Modelling and Forecasting Saudi Arabia's Inbound Tourism Demand

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Abstract

The tourism sector in Saudi Arabia has been identified as one of the priority sectors in Saudi's Vision 2030. This vision is focused on diversifying the economy, contributing to economic growth (of more than 10 per cent), and creating one million jobs by 2030. The Saudi tourism industry has recently witnessed a spectacular expansion in recent years due to the introduction of clear and specific policies and institutional structures. However, for effective tourism management strategy and planning, appropriate policy decisions and infrastructure development, there needs to be a greater understanding of what factors influence international tourism demand. Motivated by this need, this study has three main objectives: to identify the impact of the main determinants (both economic and selected non-economic factors) of inbound tourism demand; to forecast inbound tourism demand; and to assess and project the impact of the COVID-19 pandemic on international tourist arrivals to Saudi Arabia.

To address gaps in the body of knowledge, this study introduces country-specific factors into tourism demand models, including human rights issues, destination prosperity, students studying abroad, and expatriate workers. This study also fills gaps in existing knowledge by developing holistic models focused on an analysis of specific tourism market segments: religious, business, and visiting friends and relatives (VFR). To obtain robust results, this study used both static and dynamic panel estimators to measure the effects of both economic factors and selected non-economic factors on tourist flows to Saudi Arabia, from 2000 to 2019. The latest econometric models, time-series models, and two combined forecasting methods were employed to generate within-sample forecasts. To test whether a combined forecast model could outperform the individual model forecasts, root mean squared error (RMSE) and mean absolute percentage error (MAPE) approaches were used to measure forecast accuracy. Finally, scenario analysis, impulse response functions (IRF), and quantile regression (QR) were conducted to assess the impact of the COVID-19 pandemic health shock on tourism demand in Saudi Arabia during 2020 and 2021.

The results indicate that the income of the tourist origin countries, the income of the destination country (Saudi Arabia), travel costs, the cost of living at the destination (tourism price), investment in the tourism sector, political risks, and destination prosperity impacted all tourist market segments. In addition, word-of-mouth, visa restrictions, and relative temperature had a significant impact on religious tourism demand. Increased government respect for human rights had a positive and significant effect only on religious and business tourism. Trade openness had a positive and significant effect on business tourism, and Saudi students studying abroad had a positive and significant impact on VFR tourism. The number of expatriate workers had a positive and significant impact on business and religious tourism demand but a negative effect on VFR tourism. The results suggest that business tourists were more sensitive to health risks than religious and VFR tourists between 2000 and 2019.

When comparing econometric and time series model forecasting, time series models provided more accurate forecasts for religious and business tourism demand, whereas the econometric model provided more accurate forecasts for VFR tourism. The combined forecast method produced more accurate predictions only for business and VFR tourism.

Scenario analysis was useful for assessing the short-term impact of COVID-19, whereas the IRF may be useful for understanding the long-term impact. This study indicates that the COVID-19 outbreak significantly and negatively influenced Saudi Arabia's tourism industry, as travel restrictions and bans were imposed by governments across the globe. The study also shows that religious tourism was the most affected by the pandemic and needed the longest time to recover, whereas business tourism recovered relatively rapidly. The QR model indicated that the negative impact of confirmed COVID-19 cases was more at the lower quantiles of tourism demand, while there was less negative impact at the higher quantiles.

The findings of this study may assist in developing Saudi Arabia's tourism sector and economy by providing knowledge to policymakers, investors, and tourism promoters. This will enhance the development of tourism policies and increase the number of international tourists, a central goal of Vision 2030 to diversify the Saudi economy.

Declaration

I, Eman Alanzi, declare that the PhD thesis entitled *Modelling and forecasting Saudi Arabia's inbound tourism demand* is no more than 80,000 words in length including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work. I have conducted my research in alignment with the Australian Code for the Responsible Conduct of Research and Victoria University's Higher Degree by Research Policy and Procedures.

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STATEMENT OF CONTRIBUTION TO CO-AUTHORED PUBLISHED PAPER

There is a co-authored paper in chapter five. The co-authored paper reference, including all authors, is as follows:

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My contribution to the paper represents 80% of the whole, involving the provision and cleaning of data, the analysis, structuring of the paper, writing, preparation of tables and figures, and addressing most of the reviewers' comments.

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List of acronyms and abbreviations

AIDS	Almost Ideal Demand System
AIC	Akaike Information Criterion
ARDL	Autoregressive Distributed Lag
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ARIMAX	The autoregressive integrated moving average with explanatory variable.
ARX	Autoregressive-exogenous
BSM	The basic structural model
BVAR	The Bayesian Vector Autoregressive
CEPII	French Centre d'Etudes Prospectives et d'Informations Internationales
CPI	Consumer Price Index
CSM	Casual structural model
DOLS	Dynamic Ordinary Least Squares
ECM	Error Correction Model
FDI	Foreign Direct Investment
FE	Fixed Effect
FMOLS	Fully Modified Ordinary Least Squares
GaStat	General Authority for Statistics
GDP	Gross Domestic Product
GMM-DIFF	Difference Generalised Method of Moment
GVAR	The Global Vector Autoregressive
HQC	Hannan-Quinn Criterion
IMF	International Monetary Fund
IRF	Impulse Response Function
JB	Jarque-Bera
KSA	Kingdom of Saudi Arabia
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
OECD	Organisation for Economic Cooperation and Development
OLS	Ordinary Least Squares
Pooled OLS	Pooled Ordinary Least Squares
PACF	Partial Autocorrelation Function

PPML	Poisson Pseudo-Maximum Likelihood
QR	Quantile Regressions
RE	Random Effect
RMSE	Root Mean Squared Error
SA	Simple Average Combination
SARIMA	The seasonal autoregressive integrated moving average
SBC	Schwarz Bayesian Criterion
SV2030	Saudi Vision 2030
STSM	The structural time series model
TVP	Time-varying parameter
UNWTO	United Nations World Tourism Organisation
VACO	Variance-Covariance Combination
VAR	Vector Autoregressive
VFR	Visiting Friends and Relatives
VECM	Vector Error Correction Model
WDI	World Development Indicators
WUPI	World Pandemic Uncertainty Index
WTTC	World Travel and Tourism Council

CHAPTER 1: INTRODUCTION

1.1. Introduction

This chapter introduces the research presented in this thesis, which is focused on modelling and forecasting Saudi Arabia's inbound tourism demand. Section 1.2 provides the background to the study and Section 1.3 outlines the research problem. Section 1.4 presents the study questions and Section 1.5 explains the study's aim and objectives. Section 1.6 discusses the contributions to knowledge of the study and Section 1.7 discusses its significance. Section 1.8 presents delimitations of the study and Section 1.9 provides an overview of the research methodology. Finally, Section 1.10 outlines the structure of the thesis.

1.2. Background

Since the end of the Second World War, global tourism has become one of the largest economic activities in many developed and developing countries. In 2019, for example, travel and tourism generated around 10.6 percent of total employment, contributed 10.4 percent of overall GDP and generated United States dollars (USD) 1.7 trillion in tourist exports (6.8 percent of total exports, 27.4 percent of global services exports) (WTTC, 2021a). Tourism stimulates new infrastructure development and generates tax and fee revenue in developing countries. International tourism improves world peace by encouraging peacekeeping and bridging civilizations (Alola et al., 2021; Eilat & Einav, 2004). Despite periodic shocks, worldwide visitor arrivals have grown from 278 million in 1980 to 682.1 million in 2000 and 1.4 billion in 2018. With rapidly growing global tourism, countries that depend on this industry face new challenges and opportunities in planning and managing tourism. This includes the Kingdom of Saudi Arabia (KSA), which is the focus of this research.

Saudi Arabia has implemented a strategic plan to diversify its economy (rather than depending on volatile oil revenue), giving priority to the tourism sector. As part of Saudi Arabia's ambitious Vision 2030 project, tourism is seen as the leading sector in the creation of jobs, a source of foreign exchange, and key to economic development. Tourism is a composite product created by multiple industries in an economy, including food and beverages, accommodation, transportation, trade, travel, and other goods and services (Croes, 2000). Due to the importance of tourism in terms of job creation, economic growth, foreign exchange revenues, and poverty alleviation, many developed and developing countries are exerting significant efforts to attract more tourists. Several economies depend on tourism, which has become a growth engine for these countries. Being a composite outcome of labour-intensive economic activities, tourism generates huge sums of domestic income and export earnings while giving many direct and indirect employment possibilities. Moreover, several tourism-related enterprises in many developing countries are held by individuals, families, or small- to medium-sized businesses. Therefore, in many developing nations, tourism has become a strategy for decreasing poverty and diversifying the economy (Mahadevan et al., 2017; Muhanna, 2007a, 2007b; Scheyvens & Russell, 2012; Zhao & Ritchie, 2007). Numerous developing countries have created tourism development strategies or plans. To implement these, countries must estimate visitor arrivals and understand the underlying factors influencing tourism demand. Increasingly, authorities responsible for tourism planning and investment or strategies require comprehensive studies on pull and push factors in tourism to help forecast demand.

Saudi Arabia is the largest destination in the MENA region. [1] It is also a major Muslim pilgrimage centre (UNWTO, 2019c). Most of Saudi Arabia's wealth comes from oil revenues. The country is the founder and primary member of the OPEC (Organization of the Petroleum Exporting Countries) group and is a G20 member (Alshammari, 2018). Like other Arab countries in the Middle East, Saudi Arabia depends on natural resource exploitation, its Islamic heritage, Arabic culture and customs, rapid urbanisation, migrant labour, and policies for economic diversification (Alshammari & Shaheen, 2021).

The Travel and Tourism Council (WTTC) (2021b) reported that the Middle East was the second fastest-growing area in 2019 behind the Asia Pacific, with travel and tourism GDP (percentage of global GDP), growing by 3.2 percent. This growth was largely driven by Saudi Arabia, which is the region's largest country in terms of travel and tourism GDP, with growth reaching 11.7 percent. It was also the fastest growing economy in 2019, not just in the Middle East but also among the G20 economies. This rapid development was the result of Vision 2030, mentioned above, designed to advance the transformation of the travel and tourism industry.

Since 2011, Saudi Arabia has improved its position on the global prosperity index rankings, including in well-being, safety and security, personal freedom, living conditions, health, education, governance, social capital, investment environment, entrepreneurial conditions, market access and infrastructure, economic quality, and the natural environment. However, while Saudi Arabia performs well on enterprise conditions, education and social capital, it still rates very low on personal freedom, a rating that has been widely criticised. It is consistently ranked among the worst countries in terms of human rights, political and civil rights, with abuses including torture, failure to uphold women's rights, the guardianship system, segregation, and restrictions on the rights of foreigners, migrant workers, labourers, freedom of the press and communication, and political freedom. Naturally, these criticisms have an impact on global perspectives when it comes to visiting Saudi Arabia (Abuhjeeleh, 2019). In order to 'normalise' international perceptions of the country, Saudi Arabia has recently made changes,

[1] Countries of the Middle East and North Africa.

such as making it easier for women to participate in public life with the right to vote and the freedom to leave the house without being accompanied by a male relative.

Tourism has recently experienced significant growth due to the implementation of effective, clear policies and an institutional structure (Khan, 2020). The Saudi Ministry of Tourism, establised in 2019, has eliminated certain social restrictions, including the requirement for couples to prove they are married before they can share a hotel room, and it is no longer a requirement for foreign women to wear long robes in public. Women can also now rent hotel rooms without the consent of their male relatives (Ahmed, 2021). The Saudi government also introduced labour reforms in March 2021 to improve the conditions of migrant workers. This change is reflected in recent international indicators and reports that show enhanced human rights scores.

As part of the Vision 2030 strategy, a focus on tourism would encourage the country to welcome international leisure visitors, to make the country a top-five destination in the world and to attract more than 100 million tourists per year by 2030 (Khashan, 2017). To meet its targets, a comprehensive quantitative study to help forecast tourist arrivals and determine the factors that influence tourism demand is fundamental to the country's strategic planning and investment. This will help ensure Saudi Arabia becomes an attractive destination for both citizens and visitors, promoting Vision 2030 with a focus on prosperity and enhanced quality of life in the kingdom.

1.3. Research problems

A number of notable characteristics have been identified in the literature on tourism demand modelling. Firstly, tourism demand literature has a geographical bias due to the fact that most studies have concentrated on the industrialised markets for both sources and destinations, while other regions have been given less attention in the literature (Claveria, 2017; Peng et al., 2014; Peng et al., 2015). In particular, less attention has been paid to tourism demand in the Middle East where Saudi Arabia is located. International tourism demand for Saudi Arabia is different from that of other countries. Saudi Arabia has key religious sites, and it is an oil-rich country, with Vision 2030 providing a road map towards a new economy, bestowed with diverse tourist destinations and thus great tourism potential. Only a limited number of studies have examined the determinants of tourism demand and forecast tourism demand in oil-based countries, particularly those in the Arabian Gulf. This study focuses on Saudi Arabia as an emerging destination for visitors to the Middle East, therefore it expands the scope of knowledge to include a greater geographical context.

Secondly, there are factors that can affect tourism demand that have not been examined before. Tourism is usually influenced by both economic and non-economic factors. There is a wide variety of factors that can affect tourism demand that goes beyond price and income. The demand for tourism has been associated with various explanatory economic factors, which have been reviewed in numerous studies. These factors include income, the relative price of tourism, the price of tourism in substitute destinations, travel costs, living costs, and exchange rates (Agarwal et al., 2021; Dritsakis, 2004; Kadir & Karim, 2009; Lee et al., 2021; Li et al., 2006; Paniagua et al., 2022; Santana-Gallego & Fourie, 2020; Shen et al., 2011; Sokhanvar et al., 2018; Song & Li, 2008). But other non-economic factors should also be taken into account. Yet, non-economic factors have rarely been incorporated in the tourism demand models of previous studies. Non-economic factors such factors related to the destination or origin country or the relationship between them. Some early studies have shown that specific factors attract tourists to a particular destination, such as political stability (Afonso-Rodríguez, 2017; Ahad et al., 2021; Altindag, 2014; Balli, Uddin, et al., 2019; Basu & Marg, 2010; Ghalia et al., 2019; Samitas et al., 2018), personal safety (Saha et al., 2017), the lack of terrorism, crime and corruption (Bassil et al., 2019; Basu & Marg, 2010; Drakos & Kutan, 2003; Feridun, 2011; Fletcher & Morakabati, 2008; Fourie et al., 2020; Harb & Bassil, 2020b), climate (Day et al., 2013; De Freitas et al., 2008; Eugenio-Martin & Campos-Soria, 2010; Goh, 2012; Hamilton & Tol, 2007; Jermsittiparsert, 2020), the availability of transportation infrastructure and services (Adeola & Evans, 2020; Athanasopoulos & Hyndman, 2008; Gholipour, Andargoli, et al., 2021; Habibi, 2017; Khadaroo & Seetanah, 2008; Nguyen, 2021), political and economic freedom (Saha et al., 2017), governance and institutional quality (Tang, 2018), life expectancy as a proxy of human development (Naudé & Saayman, 2005; Rosselló et al., 2017; Viljoen et al., 2019), levels of happiness at the destination (Gholipour et al., 2022; Huang et al., 2021), cultural and geographical variables (Azimi Hashemi & Hanser, 2018; Yang & Wong, 2012), minimal health risks (Rosselló et al., 2020; Rosselló et al., 2017), and trends in immigration patterns (Balli et al., 2016; Balli, Ghassan, et al., 2019; Seetaram, 2012; Seetaram & Dwyer, 2009).

Saudi Arabia's Vision 2030 focuses on promoting prosperity and well-being, making it a critical factor in attracting both citizens and visitors to the country. Previous research has already established the importance of various factors, such as freedom, security, happiness, environment, strong institutions, and quality of governance, in influencing international tourism demand. However, one crucial aspect that has been overlooked in previous research is the comprehensive investigation of how a destination country's prosperity directly affects inbound tourism demand. Country prosperity goes beyond economic indicators and encompasses a destination's social well-being and ability to generate sustainable benefits for local communities, businesses, and the environment. This holistic approach is crucial as it determines a destination's capacity to provide economic opportunities and improve the quality of life for residents while safeguarding its natural and cultural heritage. Tourism demand is likely higher when a destination experiences economic growth and prosperity. The reason for this is that a prosperous destination is able to provide tourists with a wide variety of products and services tailored to their needs and preferences. An economically prosperous destination may, for instance, offer better infrastructure, a greater selection of high-quality accommodation, and more diverse attractions.

Therefore, this study explores whether the destination prosperity level influences inbound tourism demand. To achieve this, the Legatum prosperity index was used to provide a unique insight into how global prosperity is developing (Sokhanvar et al., 2018). This index is the most comprehensive indicator and represents the only worldwide measure of prosperity that considers well-being and income.

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However, despite Saudi Arabia's prosperity and robust economy, the tourism industry faces significant challenges. As noted earlier, one of these challenges is that the government’s human rights policies have received international criticism. Ricci (2021) argues that the lack of respect for human rights and individual freedom, particularly when it comes to women's rights, affects the country's reputation. Therefore, this study also tests the impact of human rights on tourism demand.

Previous studies (Dwyer et al., 2002; Etzo et al., 2014; Massidda et al., 2015; Seetaram, 2012; Seetaram & Dwyer, 2009) have investigated the impact of immigrants on inbound tourism demand in Italy and Australia. However, expatriate workers living in Saudi Arabia and Saudi students stying oversea have been overlooked as potential determinants of tourism demand. Importantly, expatriate workers living and working in Saudi Arabia represented about 38.3 percent of the country’s total population in 2019 (Balli et al., 2018; ICEF, 2022; Central Intelligence Agency, 2019). Saudi Arabia is the third-largest country of destination for international expatriates globally, with 13.4 million people, following the United States of America with 51 million migrants and Germany with 15.3 million (Chandramalla, 2022). In 2016, there were more than 100,000 Saudi Arabian students studying abroad, The Kingdom of Saudi Arabia is ranked fourth (preceded by China, India, and South Korea) in the number of students studying abroad. The King Abdullah Scholarship Program (KASP), initiated by the Saudi government in 2005, serves as a crucial catalyst for this upward trend. Its primary objective is to foster cultural exchange that mutually benefits both Saudi Arabia and the host country (Taylor & Albasri, 2014).

Saudi students studying abroad can have a considerable impact on inbound tourism demand, particularly within the visiting friends and relatives (VFR) segment. Students are likely to influence tourism by visiting their home countries repeatedly during study periods, Moreover, their presence in foreign countries enables them to develop a global mindset and establish a network of international friends, which can serve as an additional source of potential visitors to Saudi Arabia. Through their interactions and relationships, these students can introduce and promote Saudi Arabia as an appealing travel destination, attracting visitors who may not have otherwise considered the country.

Furthermore, Saudi students studying overseas can serve as valuable resources for travel information, offering guidance on travel itineraries, accommodation, local customs, and attractions. Their firsthand knowledge and experiences enhance the planning process and create more convenient, enjoyable, and culturally immersive visits. The study by Davari and Jang (2023) emphasises the significance of intercultural interactions before international travel and highlights the potential role of individuals from different nations as tourism and cultural ambassadors beyond their homelands. By fostering cross-cultural relationships, these ambassadors contribute to a deeper understanding and appreciation of diverse cultures, encouraging more meaningful and enriching travel experiences for explorers of new destinations.

Indeed, students are likely to influence tourism by effectively promoting their home countries among their friends in the destination countries, effectively serving as informal advertisers for Saudi Arabia. This valuable word-of-mouth effect can further bolster inbound tourism demand. In conclusion, the presence of Saudi students studying abroad creates an opportunity to positively impact inbound tourism to Saudi Arabia, particularly within the VFR segment. Their global outlook, international friendships, and role as cultural ambassadors can effectively promote the country as a desirable travel destination, while their firsthand knowledge enhances the travel experience for visitors.

Expatriate labourers may explicitly or implicitly promote their temporary destination to those in their home country. This promotion could encourage relatives or friends to visit or even work in the temporary destination. A number of researchers (Balli et al., 2018; Balli, Ghassan, et al., 2019; Divisekera, 2003; Dwyer, 2002; Seetaram, 2010, 2012; Seetaram & Dwyer, 2009; Senadeerage, 2020) have found that immigrants who live in another country seem to stimulate international travel between the country of origin and the temporary destination. Given the large numbers of Saudi students studying abroad, and the many expatriate workers in Saudi Arabia, it is important to understand how these cohorts influence tourism demand. These variables associated with the destination country are included in this thesis to investigate their effect on inbound tourism demand.

Thirdly, there have been many studies examining the relationship between international tourism demand and its determinants in general (total), but few studies have categorised tourist arrivals into specific types of visit purposes, such as holiday, business, VFR, studying, attending conventions, health, and religious purposes (Chen, 2019; Cortés-Jiménez & Blake, 2011; Senadeerage, 2020; Turner & Witt, 2001), and compared these variations in detail to determine how tourists respond to various factors based on the purpose of their visit.

Fourthly, this study focuses on the modelling of religious tourism. While demand modelling in the field of tourism has primarily concentrated on VFR and leisure and holiday segments, there has been limited research specifically addressing the demand for religious tourism. Chapter two of this thesis provides insights into the unique aspects of religious tourism in Saudi Arabia. Religious tourism, characterised by its distinct features, has received minimal attention in the existing academic literature. By examining the demand for religious tourism, this research aims to fill the gap in knowledge and understanding in this area. It explores the factors that drive the demand for religious tourism, including pilgrimage, religious events, and attractions of religious significance.

Fifthly, little attention has been paid to forecasting tourism demand to Saudi Arabia. To achieve a more reliable and accurate forecast, this study employed time series, and econometrics with new independent variables and combined them to compare the accuracy between various forecasting models based on the purpose of visit.

Even though COVID-19 impacted all tourism demand negatively, the setting of containment measures differed in terms of timing, length, characteristics, geographical area (region and country) (Plzáková & Smeral, 2022) from country to country. This study focuses on the COVID-19 effects on Saudi Arabia at the disaggregated level based on the purpose of visit and compares the impact of COVID-19 on specific visit purposes. Finally, Previous studies on tourism in Saudi Arabia primarily focused on its development, enhancement of tourism and the link between tourism and economic growth. These have been analysed by Ageli (2013), Alodadi and Benhin (2015a, 2015b), Alodadi (2016), Altaee et al. (2016), Bokhari (2018), and Kouchi et al. (2018). However, little attention has been paid to the factors that determine international tourism demand.

Therefore, the primary objectives of this study were to investigate the factors that influence international tourist inflows from origin countries to Saudi Arabia for three types of visits and to evaluate the forecasting performance of time series, econometric methods, and combined time series and econometric methods over different forecasting horizons (from 2017 to 2019). This investigation sought to improve our understanding of the major economic and non-economic factors that impact tourism demand from origin nations to Saudi Arabia, serve as the foundation for developing robust forecasting models for tourism demand, and identify the impact of the COVID-19 pandemic on religious, business and VFR tourism demand.

1.4. Research questions

The previous section identified several gaps in the tourism demand modelling and forecasting literature in general and in Saudi Arabia in particular. By focusing on Saudi Arabia as a case study, this thesis addresses the following important research questions to fill the existing literature gaps:

1. Do economic variables, including the incomes of both destination and origin countries, the cost of living in the destination, travel costs and capital investment in the tourism sector in the destination country impact the total number, religious, business, and VFR tourists travelling to Saudi Arabia?
2. Do foreign direct investment (FDI) and trade openness variables impact business and the total number of tourists travelling to Saudi Arabia?
3. Do non-economic variables, including political risk, human rights, global health risks, relative temperature, destination prosperity and expatriate workers impact the total number, religious, business, and VFR tourists travelling to Saudi Arabia?
4. Do word-of-mouth, visa restrictions and Hajj incident variables impact religious tourists travelling to Saudi Arabia?
5. Do international Saudi students studying overseas, and visa restriction variables impact the total number and VFR tourists travelling to Saudi Arabia?
6. Does the importance of such factors vary in accordance with the purpose of the visit?
7. Does the econometric method provide more accurate forecasting than the time series method?
8. Does the combined forecast method provide more accurate forecasting than the individual forecast method?
9. How do religious, business and VFR tourists travelling to Saudi Arabia respond to the COVID-19 pandemic?

1.5. Objectives of the study

In line with the research questions, this study aimed to model and forecast Saudi Arabia's inbound tourism demand and assess the impact of the COVID-19 Pandemic on Saudi tourism demand for disaggregate travel purposes. To fulfil this aim, the objectives were to:

1. Develop more holistic models for economic and selected non-economic factors to identify their impact on the total number, religious, business, and VFR tourist flows to Saudi Arabia.
2. Identify the importance of economic and select non-economic factors on international tourism demand at aggregate and disaggregate levels.
3. Use time series models, econometric models, and a combination forecast method to generate ex-post forecasting of religious, business, and VFR tourist arrivals to Saudi Arabia.
4. Compare the performance of forecasting models to provide the best possible forecast methods for how international tourism flows work in Saudi Arabia.
5. Assess the impacts of the COVID-19 pandemic on religious, business, and VFR inbound tourism demand for Saudi Arabia.

1.6. Contribution to knowledge

This study makes several theoretical contributions. Firstly, this thesis contributes to expanding the knowledge of tourism in Saudi Arabia as an important emerging tourist destination in the Middle East. Previous studies have focused on Western countries or Asian and African countries (Kon, 2002; Shafiullah et al., 2019; Syriopoulos, 1990; Uysal & Crompton, 1984; Veloce, 2004; Viljoen et al., 2019; Zhou-Grundy, 2011) while developing countries, particularly in oil-based nations, have received very little attention (Kumar & Kumar, 2019; Wamboye et al., 2020). Tourism demand differs based on location and economic structure. Therefore, modelling inbound tourism demand in Saudi Arabia is important for understanding how an oil-based economy might affect international tourism.

Secondly, this study introduces new variables such as human rights, the prosperity of the destination, international students and foreign workers to examine the impact of both economic and non-economic factors on inbound tourism demand in Saudi Arabia.

Thirdly, this study highlights the differences in response to these factors by various types of tourists: religious, business, and VFR tourists. Thus, this study can improve our understanding of the sensitivity of different groups to changes in the independent variables.

Fourthly, since there is no study on forecasting tourism demand in Saudi Arabia and empirical evidence suggests that forecasting accuracy varies across the destination, source market pairs, and explanatory variables (Song et al., 2019), this current study fills a gap in the literature. It does this by applying a time series model, econometric models and combined forecasting of econometric and time series methods to evaluate accuracy of forecasting. Since this is the first study in forecasting tourism demand in Saudi Arabia, forecasts generated by these models will provide useful policy inputs to the country's tourism development strategy.

Lastly, since there is little investigation to date that has sought to estimate or separate the effects of a pandemic on diverse types of tourism demand, this study proposes a research framework that separates the respective effects of COVID-19 on three types of tourism demand (religious, business and VFR) to estimate the degree of their response to the pandemic.

1.7. The practical contribution of the study

Saudi Arabia's government, tourism sector, and other related sectors and policymakers can use the knowledge of factors that significantly influence international tourism demand to develop strategies for promoting a higher level of tourism in the country. In order to develop effective marketing strategies, it is critical to understand why people decide to travel and what influences their choice of destination.

This study provides insights for government planners, business developers, tourism marketers, legislators, academics, and specialists in the travel and hospitality sectors to assist them in developing promotional programs, logistical plans, infrastructure facilities policies, and workforce distribution. Since religious tourism demand consists of a high percentage (60 percent) of total tourism demand and other kinds of tourism are expected to grow as a result of Vision 2030, it is necessary to identify the factors related to each of these disaggregate markets in order to plan strategically for each tourist type separately.

Accurate forecasting in international tourist arrivals is essential for tourism planning and policymaking and imperative for destination management, infrastructure development, and tourism investments. The development of policies and plans is particularly important in managing the resources available to support development initiatives and efficiently allocate scarce resources.

Tourism policymakers need to understand the impact of COVID-19 on inbound tourism to manage the risk. Both destination policymakers and scholars would be interested in an assessment of the influence of the COVID-19 pandemic on tourism at the country level. Such an assessment would assist the former to design appropriate policies aimed at minimising the impacts of such or similar crises, while the latter will be able to develop appropriate methods of assessing the individual event impacts on tourism. This information facilitates the incorporation of driving factors into the econometric model and improves the understanding of past events.

1.8. An overview of the research methodology

Chapter five: In this chapter, the importance of economic factors (the income of both origin and destination countries, the cost of living in the destination, travel costs, capital investment in the tourism sector, FDI, and trade openness) and non-economic factors (word-of-mouth, expatriate workers, Saudi international students, political risk, human rights, global health risk, relative temperature, and destination prosperity) for international tourism demand modelling is investigated. This is done at a disaggregate level by purpose of visit considering religious, business and VFR tourism demand in Saudi Arabia, along with an aggregate model for comparison purposes. This chapter involves panel data analysis, generalised method of moment (GMM-DIFF), and panel autoregressive distributed lag (ARDL) model annual data from 2000 to 2019 from major source countries for disaggregate and aggregate tourism demand model respectively.

Chapter six: In this chapter, forecasting models are presented for religious, business and VFR growth rates for international tourist arrivals and for arrivals from market share source countries. The following models were used in this study: autoregressive moving average (ARMA), simple exponential smoothing, naive-1, an error correction model (ECM), and the vector autoregressive (VAR) model. The forecasting performance of these models are then compared to a simple average combination (SA) method and a variance–covariance combination (VACO) method to provide more accurate forecasting.

Chapter seven: This chapter presents the quantile regression employed in this study to analyse the relationship between COVID-19 and religious, business and VFR tourism in Saudi Arabia using monthly data from January 2020 to December 2021 (the COVID-19 peak period). This chapter also discusses the impulse response function (IRF) based on a VAR model to track the dynamic impact of a shock system or changes in tourism demand determinants (income and health risks) by using annual data from 2000 to 2019. Scenario analysis is also presented in this chapter, designed to assess the impact of COVID-19 on religious, business and VFR international tourists to Saudi Arabia. This was achieved by conducting tourism demand projections during the uncertainty period across several scenarios. Several possible changes in the tourism demand determinant (income and health risks) were assumed in the uncertainty period of 2020 and 2021.

1.9. Delimitations

The United Nations World Tourism Organization (UNWTO) has sought to standardise tourism terms and classifications worldwide. The UNWTO's definition of tourists is people who travel to and stay in places beyond their typical environment for leisure, business, and other reasons, for no more than one year. Visitors are called international tourists if their travel destination is outside their own country. Domestic tourism refers to travel within a given country by its residents.

International tourism can be classified into two types based on the direction of travel flows: inbound and outbound tourism. Inbound tourism refers to non-residents visiting the destination country. Outbound tourism refers to the actions of residents of a certain country who travel to and stay in destinations other than their home country and their usual environment.

As implicit above, a place where one stays for more than a year is considered a residence rather than a tourist attraction. In terms of the minimum length of stay, a person is classified as a tourist if they spend at least one night (24 hours or more) in the destination. If they stay for less than 24 hours, they are classified as a same-day visitor or excursionist, such as a cruise passenger. This study focused on inbound international tourists to Saudi Arabia.

The reasons, purposes or motivations for travelling include pleasure, recreation and holidays, VFR, business and professional, health treatment, religion or pilgrimages, sport, and so on. Because visitors travelling for different reasons have varied decision-making characteristics, analysis at the disaggregated level is more significant. Religion, business, and VFR are the top three reasons for visiting Saudi Arabia, according to the data in this study.

Religion/Hajj tourism: This category includes, but is not limited to, attending religious meetings and events and participating in the Hajj or Umrah. The religious highlight of every Muslim’s life is the pilgrimage to various holy areas of Saudi Arabia. Muslims are required to perform the Hajj at least once in their life unless they are financially or physically unable to do so. The Umrah is similar to the Hajj and can be done at any time of the year.

VFR: This category includes activities such as visiting relatives or friends, attending weddings, funerals or other family events, and any short-term care for the sick and elderly.

Business and professional tourism: This category includes the activities of self-employed workers and the activities of investors and businesspeople who are attending public or private meetings or conferences, trade and art exhibitions, giving lectures, holding concerts, engaging in purchasing or selling, marketing goods or services, engaging in government missions, participating in research, or engaging in military missions.

A tourist's decision to travel to a particular destination is influenced not only by economic factors, such as price and income, but also by non-economic factors, such as perceptions of a destination, its political, security, prosperity, and climatic condition. Because of this, this thesis examines the impact of economic and non-economic factors on tourism demand.

1.10. Structure of the thesis

This thesis is divided into eight chapters, as follows:

Chapter one has outlined the study context and gaps in the existing literature, as well as the research questions, objectives, and significance that guided the research.

Chapter two provides an overview of both worldwide tourism and tourism in Saudi Arabia. It also explores some tourism-related issues, the development of tourism, and its contribution to the economy.

Chapter three reviews the relevant theoretical and empirical literature on modelling and forecasting tourism demand and presents the research hypothesis.

Chapter four discusses and justifies the study's selected philosophy and the methodology used to answer the research questions and achieve the study's objectives. In addition, the chapter explains the variables measurement and data sources, as well as estimation processes.

Chapter five focuses on the results of the estimation of tourism demand to achieve the first and second objectives of this thesis, employing both static and dynamic panel analysis**.**

Chapter six outlines the main analysis findings from the combination forecasting method and compares the time series and econometric models in forecasting the rate of growth in disaggregated international tourism demand.

Chapter seven assesses the impact of the COVID-19 pandemic on Saudi Arabia's religious, business and VFR tourism demand in 2020 and 2021. This study employed quantile regression, scenario analysis and IRF to estimate the effects of the pandemic crisis on disaggregate Saudi tourism demand.

Chapter eight Summarises the objectives, highlights key findings, and discusses the theoretical contribution and practical implications of the study. Furthermore, the chapter provides recommendations for future research on this topic and discusses research limitations.

CHAPTER 2: GLOBAL AND SAUDI ARABIAN TOURISM

2.1. Introduction

This chapter sets the foundation for the rest of the thesis by presenting the background of global and Saudi Arabia tourism and the changes that have occurred. The chapter is structured as follows: Section 2.2. provides an overview of worldwide tourism, while Section 2.3. focuses only on Saudi Arabia's tourism. Section 2.4. examines the impact of COVID-19 on global tourism demand and Section 2.5. on Saudi tourism demand. The chapter concludes with Section 2.6., which summarises the discussion.

2.2. The global tourism industry

As discussed in the previous chapter, tourism has long been recognised as an essential tool for economic growth and job creation. Tourism contributes significantly to regional, national, and global economic development. It contributes to reducing imbalances in the balance-of-payments while also generating income, employment, and tax revenue (Saarinen et al., 2011; Syriopoulos, 1990).

Almost all countries make significant efforts to increase the number of international tourists in their economies. The tourism industry, in particular, plays an essential role in underdeveloped nations by providing a tool for community development, creating employment opportunities, and offering advantages to the poor and disadvantaged (Binns & Nel, 2002; Sadi & Henderson, 2005). Thus, the tourism industry is more vital for developing countries than for developed ones in terms of attaining economic and social goals, particularly the United Nations Millennium Development Goals [2].

As can be seen in Table 2.1, worldwide international tourist arrivals (millions) increased rapidly from 2009 to 2019, although the market share varied by region. Table 2.2 shows that the European region received the most international tourists, accounting for 57.6 percent of the market in 2000. Nonetheless, its market share has been declining over the years, dropping to 50.9 percent by 2019. However, despite this decline, Europe continues to rank number one in terms of its market share of international tourist arrivals. The Asian-Pacific regions have overtaken the American region [3] as the second-largest region. The American region has witnessed a sharp decline in its market share over the years: from 18.6 percent in 2000 to 15 percent in 2019.

Asia-Pacific has experienced incredible growth in international tourist arrivals and market share, increasing from 16.1 percent in 2000 to 24.6 percent in 2019, showing the best overall performance out

[2] In 2000, the United Nations Millennium Development Goals (MDGs) were a set of eight international development goals meant to reduce poverty, improve health and education, empower women, and achieve sustainable development.

[3] The American Region, also known as the Americas, is composed of North America, Central America, South America, and the Caribbean. It comprises countries such as the United States, Canada, Mexico, Brazil, Argentina, and many others.

of all regions. The Middle East's market share grew slightly from 2000, but gradually declined in 2018, reaching its 2005 level again in 2019. The African region has also shown modest growth in international tourist arrivals and market share. The lost market shares of the European, American and Middle Eastern regions have been captured by the Asia-Pacific region.

Table 2.1. International tourist arrivals (millions) from 2000 to 2019

Year	World	Africa	Americas	Asia-Pacific	Europe	Middle East
2000	687.0	28.3	128.1	110.5	395.9	24.2
2005	806.8	37.3	133.5	155.4	441.5	39.0
2015	1184.0	53.3	191.0	278.6	607.6	53.3
2017	1337.0	63.0	210.7	324.1	676.6	57.6
2018	1407.0	68.4	215.7	347.7	715.7	59.6
2019	1465.9	70.1	219.3	360.4	746.1	70

Source: UNWTO (various issues across the period from 2000 to 2019)

Table 2.2. International tourist arrival market share by region from 2000 to 2019

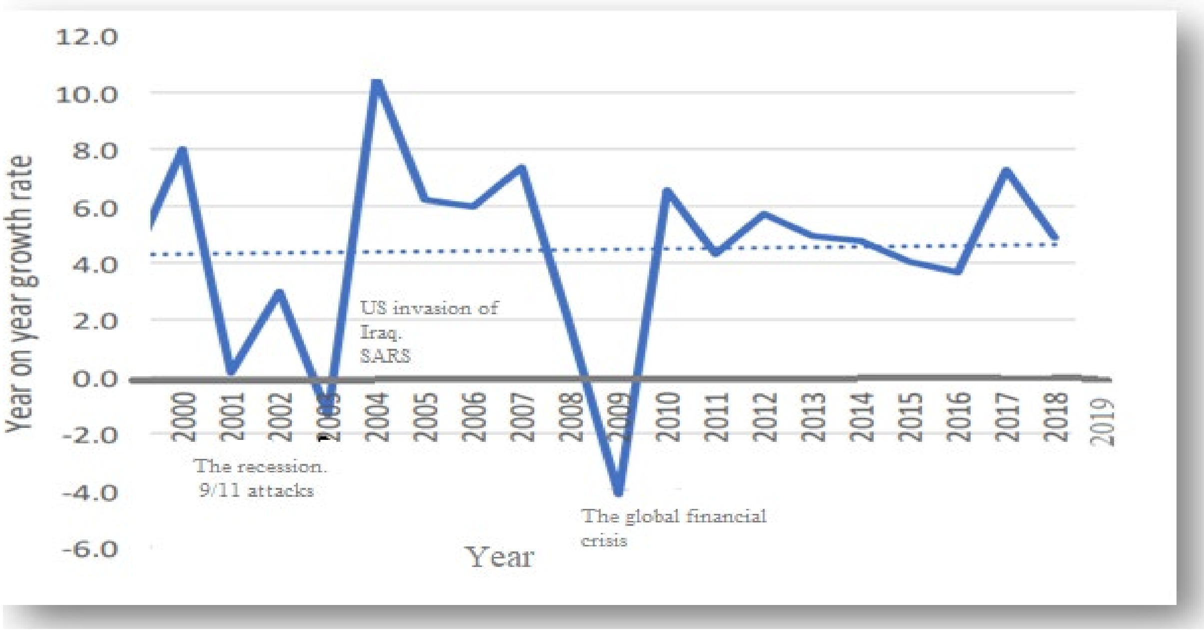
Year	Africa	Americas	Asia-Pacific	Europe	Middle East
2000	4.1	18.6	16.1	57.6	3.5
2005	4.6	16.5	19.3	54.7	4.8
2015	4.5	16.1	23.5	51.3	4.5
2017	4.7	15.8	24.2	50.6	4.3
2018	4.9	15.3	24.7	50.9	4.2
2019	4.8	15.0	24.6	50.9	4.8

Source: Calculated by using data from UNWTO annual reports (2000-2019) and UNWTO World Tourism Barometer

Since the end of World War II, global tourism has experienced several unfavourable events. In the last twenty years, this has included the recession of 2000 and 2001; the September 11 2001 attacks; the 2003 US invasion of Iraq; severe acute respiratory syndrome (SARS), a viral respiratory illness; terrorist acts in a number of countries, including Indonesia, Turkey, Russia, Columbia, and Saudi Arabia; the Global Financial Crisis of 2008 to 2009 (the 'Great recession'); and the influenza A/H1N1 pandemic, which had a significant impact on tourism markets, resulting in lower foreign visitor volumes than in prior years, as shown in Figure 2.1. Tourism is extremely sensitive to such unfortunate events, particularly in terms of security and safety risks. Despite these challenges, in general, global tourism was growing at a rate greater than four percent in 2019, as illustrated in Figure 2.1.

The rapid growth of international tourist arrivals has been fuelled by several factors, including rapid growth in the Asia-Pacific region, particularly in China, and visa relaxation. For example, approximately 75 percent of people needed traditional visas to visit a country in 1980, while this requirement fell to 53 percent in 2018 (UNWTO, 2019a). The majority of tourist destination countries, including Saudi Arabia, provide e-visas and visas on arrival to enable tourists to travel more easily. This trend is expected to continue and will have a positive impact on the global tourism industry.

Figure 2.1. Growth rate of international tourist arrivals from 2000 to 2019



Source: WTTC data

As noted earlier, international inbound tourism in the Asia-Pacific region has grown higher than in other regions. For example, the Asia-Pacific region showed the highest growth rate of seven percent both in international tourism and tourism receipts in 2018, followed by Africa (seven percent) (UNWTO, 2019b). Europe and the Middle East recorded a five percent growth in global arrivals, while the Americas reported a two percent increase. Furthermore, between 2010 and 2018, international arrivals to the Asia-Pacific area increased at a rate of seven percent per year, outpacing the global average of five percent and outperforming all other regions (UNWTO, 2019b).

2.2.1. Contribution of tourism to the world economy

This section provides an overview of the economic impact of tourism. It offers policymakers and industry stakeholders a better understanding of how tourism contributes to the local economy, so they can make informed decisions regarding its support and growth (Khan et al., 1990).

2.2.1.1. The contribution of tourism to the gross domestic product (GDP)

Tourism's overall contribution to global gross domestic product (GDP) has increased from USD 3,701 billion in 2000 to USD 9,126 billion in 2019, as shown in Table 2.3. Tourism's contribution to GDP was around 10.4 percent in 2019.

Table 2.3. Tourism contribution to GDP from 2000 to 2019

Year	Total effect (USD billion)	% of GDP
2000	3701.3	10.9
2005	4805.9	10.1
2010	6108.6	9.3
2015	7444.0	10
2016	7650.2	10.3
2017	8240.7	10.4
2018	8811	10.4
2019	9126.7	10.4

Source: WTTC data search tool (various issues across the period from 2000 to 2019)

According to the WTTC (2019b), travel and tourism contributed USD 8,811.0 billion to GDP in 2018, and grew by 10.4 percent to USD 9,126.7 billion (10.4 percent of GDP) in 2019. It is forecast to reach USD 13,085.7 billion by 2029 (11.5 percent of GDP). These figures show that global tourism is playing a vital part in the global economy and its relevance is gradually increasing. This is providing more opportunities for countries that rely on tourism to develop their economies.

2.2.1.2. The contribution of tourism to employment

Global tourism also plays a significant role in creating job opportunities. Table.2.4 shows that the total number of job opportunities provided by tourism increased from 257.3 million in 2000 to 328.2 million in 2019. According to the WTTC (2019b), in 2019, travel and tourism accounted for a 10.1 percent share of total employment. It is predicted that, by 2029, travel and tourism will contribute 420,659,000 jobs (11.7 percent of total employment), indicating that the tourism industry's role in providing employment opportunities will likely expand in the future. This will aid in the reduction of unemployment.

Table 2.4. Tourism contribution to employment from 2000 to 2019

Year	Total contribution to employment (million)	% share
2000	257.3	10.2
2005	267.4	9.8
2010	264.6	9.1
2015	296.1	9.6
2016	303.4	9.8
2017	311.7	9.9
2018	318.8	10

2019	328.2	10.1

Source: WTTC data search tool (various issues across the period from 2000 to 2019)

However, the sector offers a significant amount of informal work, partly because it is seasonal and partly because regulations, enforcement, and work organisation are lacking. The sector is a significant source of employment for women. For example, in 2019, 54 percent of all tourism industry employees were female, as opposed to 39 percent of all workers in the entire economy. It is also a key employer and entry point for young people into the labour market, despite many workers leaving the sector in search of better working conditions. It is estimated that approximately half of all tourism employees are under 35 years of age. The sector is also known for working young people harder and for longer hours than in the economy at large. The sector also employs many migrants. According to the Organisation for Economic Cooperation and Development (OECD), 25 percent of all tourism jobs are held by foreign-born individuals.

Although the tourism industry creates a significant number of jobs, it also suffers from deficient labour conditions. These include excessively long working hours, low wages, a high turnover rate, no social security, and gender discrimination, which are most prevalent in informal industries. There is informality in all nations and places. For example, the employment rate of undocumented workers in Latin America and the Caribbean is 61.4 percent and 25.1 percent, respectively, while the employment rate of undocumented workers in Asia-Pacific exceeds 75 percent. The tourism industry is characterised by shift and night work, seasonality, part-time or temporary employment, and the increasing use of outsourcing and subcontracting. A thorough assessment of these concerns is essential to ensure the industry is maximising its potential to contribute to economic development, decent work, and sustainability. As noted earlier, tourism is considered to be one of the major sources of foreign exchange earnings, revenue, employment and essential for the balance of trade in many Middle Eastern countries. In the Middle East, Saudi Arabia is the largest Arab country. In 2019, the Kingdom received around 25 percent of the Middle East tourist arrivals, as shown in Table 2.5. The figures in the table indicate the relative proportion of tourists visiting Saudi Arabia compared to other countries in the Middle East from 2015 to 2019. The fluctuations in the percentages from year to year may be influenced by various factors, such as changes in tourism policies, economic conditions, global events, and marketing efforts, among others.

Table 2.5. Middle East tourist arrivals and Saudi Arabia's share, 2015-2019

Indicator	2015	2016	2017	2018	2019
The number of tourists in the Middle East (1) (millions)	62	60	62	66	**70**
The number of inbound tourist trips (2) (millions)	18.0	18.0	16.1	15.3	**17.5**
Saudi Arabia's share of tourists in the Middle East (%)	29.0 %	30.1 %	26.0 %	23.2 %	**25.0 %**

Source: UNWTO (2022)

The next section discusses the importance of the tourism industry in Saudi Arabia, which is the focus of this study.

2.3. Tourism in Saudi Arabia

The Kingdom of Saudi Arabia has been a unique destination for Hajj and Umrah for more than 14 centuries, providing access to Islam's two holiest mosques in Mecca and Medina. With a global Muslim population exceeding 1.8 billion, Hajj and Umrah attract a significant number of Muslims worldwide. Hajj, an annual pilgrimage to Mecca, is one of the Five Pillars of Islam and is mandatory for financially and physically capable Muslims at least once in their lifetime. Umrah, a non-obligatory pilgrimage, can be undertaken at any time of the year. Both pilgrimages hold immense spiritual significance, offering Muslims an opportunity for spiritual purification, renewal, and a closer connection to God.

Saudi Arabia, as the birthplace of Islam and home to the holy cities of Mecca and Medina, plays a central role in accommodating the religious tourism associated with Hajj and Umrah. The tourism product in this context revolves around providing facilities, services, and infrastructure to facilitate the pilgrimages. The country has made significant investments in the development of hotels, transportation, healthcare, and other amenities to cater to the needs of the millions of pilgrims who visit each year.

Due to the monopolistic nature of this product, demand for Hajj and Umrah tends to be inelastic. The unique religious and spiritual significance of the pilgrimages cultivates high levels of loyalty and commitment among Muslims. As a result, the demand for these religious experiences remains strong and resilient, even in the face of price fluctuations or external changes.

The demographic composition of Saudi Arabia further contributes to the distinctive religious setting. The country has a predominantly Muslim population, with Saudi citizens constituting the majority. The Kingdom's demographic diversity encompasses a blend of ethnicities, cultures, and languages, creating a rich tapestry of experiences for visitors. Interacting with a wide range of people and immersing oneself in different traditions and customs enhances the overall tourism product.

Additionally, Saudi Arabia's demographic composition is characterised by its youthful population. A significant portion of the population is under 30 years of age, resulting in a dynamic and energetic atmosphere. This demographic dividend adds vibrancy to the tourism sector and enhances the visitor experience, as young Saudis often play key roles in hospitality, service provision, and cultural exchange. As part of its Vision 2030 goals, Saudi Arabia aims to improve all aspects of life, including health and social well-being, and raise the life expectancy at birth from 74 to 80 years by 2030.

According to Saudi Arabia's General Authority for Statistics (GaStat, 2021a), the population is approximately 35 million, with around 13 million non-nationals accounting for over a third of Saudi Arabia's population. Foreigners actively contribute to the Labor force, with many employed in the services sector (Ekiz et al., 2017). The country's prosperity is rooted in oil, and since the 1980s, it has emerged as the largest economy in the Middle East (Stephenson & Al-Hamarneh, 2017) and one of the world's top twenty economies. Heavily reliant on oil exports, Saudi Arabia has the world's second-biggest proven petroleum reserves and is one of the world's leading petroleum exporters. Its membership in the G20 and the UNWTO reflects its economic strength (Aljarallah, 2010). Saudi Arabia is a member of the Gulf Cooperation Council (GCC), which has six members: Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates (UAE). This region, which is mostly comprised of the Arabian Peninsula, does have some of the world's fastest-growing economies and seems to be unique. GCC nations share tribal history, royal connections, political associations, Bedu cultural roots, Islamic heritage, fast urbanisation, migrant labour, rentier economies, economic diversification strategies, capitalist state structures, and institutional restructuring. They are all undergoing rapid transformation, urbanisation, ultra-modernisation, globalisation, and internationalisation. The Peninsula has rich and important antiquities, similar customs through the Bedouins and other tribes, as well as trade and the natural attractions of desert and mountain coastal regions. Saudi Arabia is located in the centre of the Arab Peninsula and covers an area of 2,250,000 km^2 (Alshammari, 2022; Hasanean & Labban, 2022).

In the past, Saudi Arabia has devoted little attention to international tourism, for social, political, and economic reasons. The country had strict laws on inbound tourism and exhibited a reluctance to receive non-Islamic tourists due to cultural and social conflict (CountryWatch, 2019; Johnson, 2010; Sadi & Henderson, 2005). As an oil-rich country, there were few financial incentives for encouraging tourism. However, due to volatile oil revenue, in 2016 Saudi Arabia implemented strategies through Vision 2030 to diversify its economy. Its primary economic objectives are to enhance the private sector's contribution to GDP from 40 percent to 65 percent and to boost non-oil exports' proportion of non-oil GDP from 16 percent to 50 percent. The government has prioritised increasing international tourism to diversify the economy away from dependency on crude oil earnings (Kernshi & Waheed, 2021). Vision 2030 initiatives and the National Transformation Plan put tourism at the forefront for attracting investment and providing employment opportunities for citizens. One of its aims is to increase the tourism sector with an expectation that it will contribute 10 percent of GDP, create one million new jobs, and attract 100 million local and foreign visitors per year by 2030 (Alammash et al., 2021; Khan, 2020).

The Saudi Tourism and Natural Heritage Commission, the country's government agency in charge of tourism management, launched the electronic tourist visa program in September 2019 to allow citizens from 49 countries to visit Saudi Arabia (Mzezewa, 2019). Saudi Arabia's visa policy was previously limited to permanent employees, their eligible dependents, international business travellers, and Muslim pilgrims who could get a special pilgrimage visa (Abuhjeeleh, 2019; Bokhari, 2008).

As noted in Chapter one, in 2019, the Saudi Ministry of Tourism, which was established in 2000, announced the relaxation of some societal restrictions, such as removing the need for couples be married if sharing a hotel room, foreign women no longer being required to wear long robes (Abaya) in public, and women permitted to rent hotel rooms without the consent of a male relative, as well as allowing public musical festivals and concerts (Ahmed, 2021; Mahmood & Alkahtani, 2018). Besides expanding its major religious sites, the Saudi government has also recently launched other initiatives for its tourism-related sectors, including the growth of airports and transportation to support religious, business, and leisure activities (Aina et al., 2019).

The Saudi Tourism Authority (STA) was established in 2020 to further support the growth of tourism. It is responsible for serving the needs of tourism companies and other commercial partners in developing the tourism industry. Among its responsibilities, STA promotes the country as a leading global tourism destination, inspires travellers, and empowers partnerships. Saudi Arabia has announced the construction of a new airport in Riyadh, which will include the existing airport as well as a new one. The new airport is planned to stretch over 57 kilometres. As part of a $1 trillion initiative to boost tourism in the kingdom, the airport is expected to receive 120 million travellers annually by 2030, with six parallel runaways. There will be additional capacity for 80,000 passengers at one time and 100 million passengers a year as a result of new airport contracts (Chaouk et al., 2019).

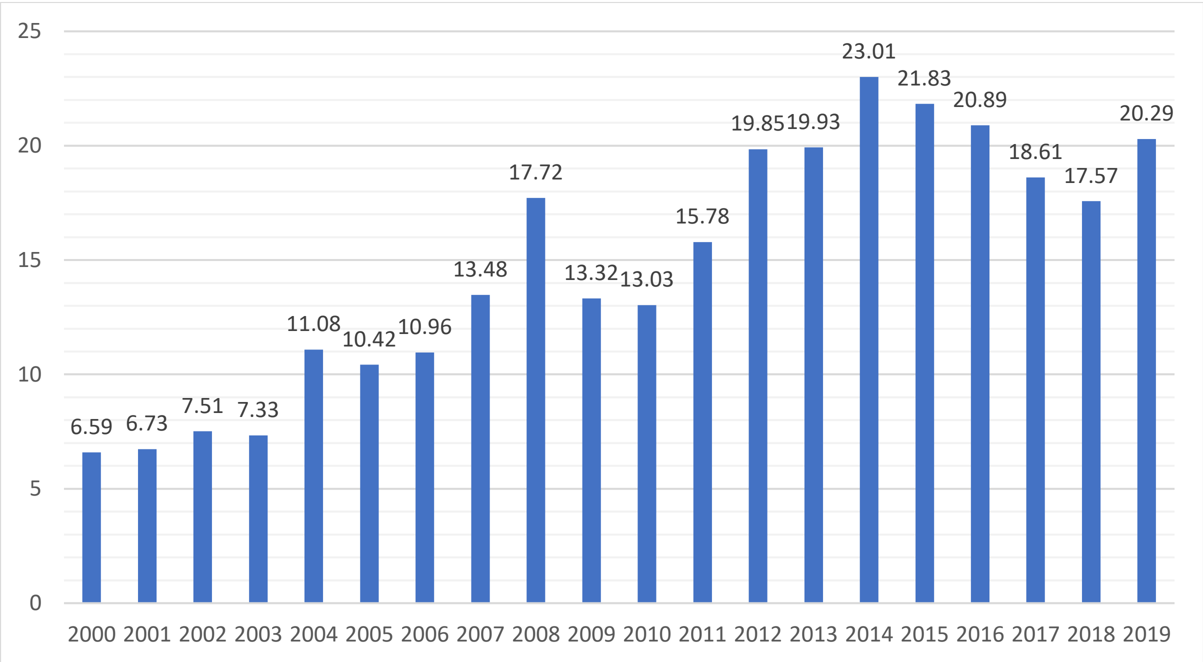
Saudi Arabia aims to attract more tourists and promote the kingdom as a tourism destination through a variety of activities. The strategy has two key objectives. First, it aims at targeting potential leisure travellers from all over the world to consider visiting Saudi Arabia for the first time. It also aims to encourage business and religious travellers already travelling to the kingdom to extend their stay so they can explore the country in a way they had not previously considered. The primary objective is to promote Saudi Arabia, both regionally and globally, by expanding the capacity to produce goods and services that will position it as a preferred tourist destination.

2.3.1. Tourism contribution to the economy in Saudi Arabia

The 2019 Global Islamic Tourism Index indicates that Saudi Arabia is the top Arab destination preferred by Muslim tourists and the fourth global destination for Muslim tourists. The head of the General Authority for Tourism and National Heritage stated that tourism in Saudi Arabia will contribute Saudi riyal[4]s (SR) 115 billion (USD 30.65) into the economy, making it one of the top five tourism destinations, and attract 100 million visitors per year by 2030. In addition, by 2030 the tourism industry could bring in 10 percent of the country's GDP, and up to 1.6 million jobs could be created.

As of 2003, tourism revenues accounted for USD 3.42 billion, or approximately 1.6 percent of the GDP, which corresponded to 7.33 million tourists and roughly USD 466 per person. It is evident that Saudi Arabia's dependence on tourism has increased significantly within the past 17 years. Before the COVID-19 outbreak, the industry brought in USD 19.85 billion, approximately 2.5 percent of the country's GDP. Therefore, each visitor spent approximately USD 978 during their trip (see Figure 2.2 and Table 2.6).

Figure 2.2. The number of tourist arrivals to Saudi Arabia (million) from 2000 to 2019



Source: UNWTO.

[4] 1 USD= 375 SAR

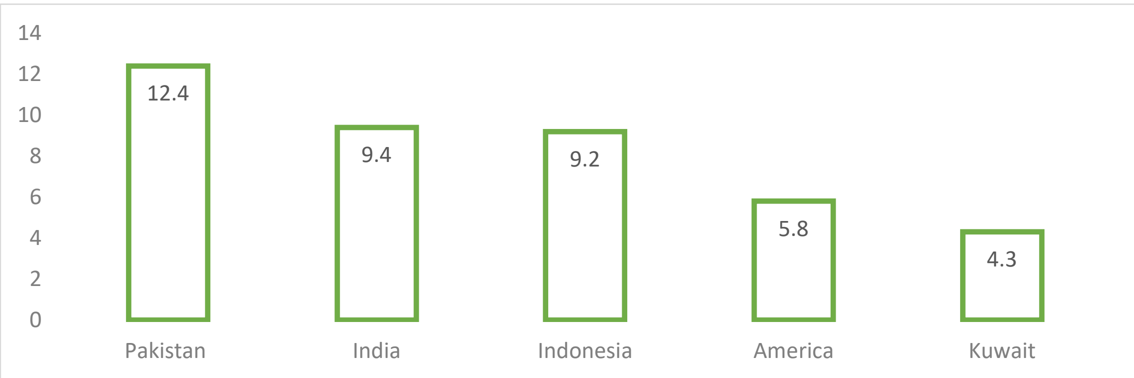
Table 2.6. Tourism revenues (USD billions) from 2003 to 2019

Year	Receipts (USD billions)	% of GDP	Receipts per tourist
2003	3.42	1.60	466
2004	6.49	2.50	585
2005	4.63	1.40	444
2006	4.77	1.30	435
2007	6.91	1.70	512
2008	6.78	1.30	382
2009	6.74	1.60	506
2010	7.54	1.40	579
2011	9.32	1.40	591
2012	8.40	1.10	423
2013	8.69	1.20	436
2014	9.26	1.20	403
2015	11.18	1.70	512
2016	13.44	2.10	643
2017	15.02	2.20	807
2018	16.97	2.10	966
2019	19.85	2.50	978

Source: UNWTO. *Note:* Tourism revenue data prior to 2003 is not available

Figure 2.3 shows the expenditure of the top five origin tourist markets. Tourist arrivals from Pakistan and India spent the most at SR 12.4 billion and SR 9.4 billion respectively, followed by Indonesia, America and Kuwait.

Figure 2.3. Expenditure of inbound tourists by nationality (billion SR) in 2019

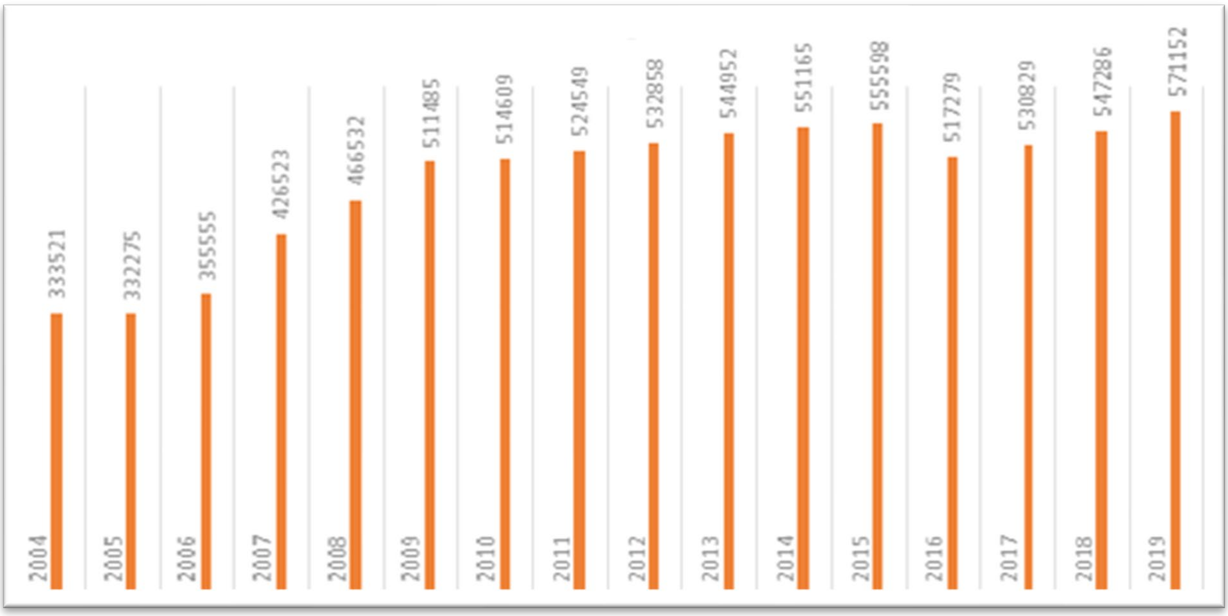


Source: Calculated from Saudi Tourism Information and Research Centre data (MAS, 2019)

According to the WTTC's annual economic impact research report, in 2019 travel and tourism directly accounted for three percent of Saudi Arabia's GDP (WTTC (2019a). The aim of Vision 2030 is to increase the GDP contribution of the tourism sector from its current rate of three percent to more than 10 percent by 2030.

Figure 2.4 illustrates that the total number of employees (direct and indirect employment) in the tourism sectors has grown since 2004 (the first year the data was available). The GaStat reported in 2019 that Saudi Arabia's travel and tourism industry's total contribution to employment was 571,152 jobs, compared with 333,521 in 2004. The tourism sector aims to create an additional million jobs in order to reach 1.6 million jobs by 2030.

Figure 2.4. Total contribution of travel and tourism to Saudi direct and indirect employment from 2004 to 2019



Source: Saudi Central Bank Functions and GaStats (various issues across the period from 2004 to 2019). *Note:* Tourism revenue data prior to 2003 is not available

In 2019, foreign visitor numbers increased significantly due to refinements to the visa-issuing system (Abuhjeeleh, 2019). In the first ten days after tourist visas were introduced, the Saudi Commission for Tourism and Antiquities (SCTA) reported 24,000 international visitors entering the country. According to the STA, the number of international visitors to Saudi Arabia reached 17.8 million in 2019, an increase of 14 percent from the previous year. The majority of these visitors were from Kuwait, the UAE, and Jordan in the Middle East; Western countries such as Canada, the US and the United Kingdom (UK); and Asian countries including Singapore, Japan, Korea, Malaysia, and China.

2.3.2. The origin of tourists to Saudi Arabia and purpose of visit

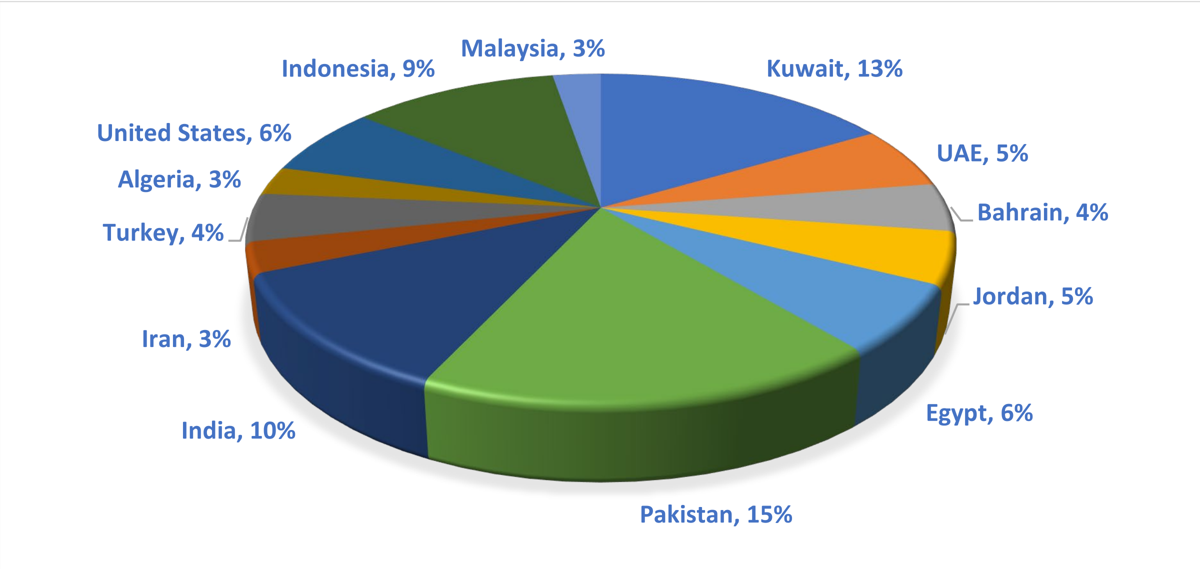
In general, the large flow of tourist arrivals to Saudi Arabia can be explained through connections of language or culture, religion, economics and/or politics. Pakistan, Kuwait, Egypt, Indonesia, the UAE, Jordan and Bahrain share similar traits and are Saudi Arabia's top inbound tourism markets, as shown in Table 2.7. The top ten countries accounted for 68 percent of total tourist arrivals in 2019.

Table 2.7. Saudi top 10 inbound tourism markets - Country ('000 trips) for 2016 and 2019

	Country	Tourist trips	Market share %		Country	Tourist trips	Market share %
2016				**2019**			
1	Pakistan	2,182	12	1	Pakistan	2,211	13
2	Kuwait	2,064	11	2	Kuwait	2,132	12
3	India	1,656	9	3	India	1,571	9
4	Egypt	1,622	9	4	Indonesia	1,429	8
5	Indonesia	1,145	6	5	Egypt	1,100	6
6	UAE	948	5	6	America	894	5
7	Jordan	920	5	7	Jordan	837	5
8	Bahrain	918	5	8	UAE	784	4
9	Turkey	691	4	9	Bahrain	511	3
10	Qatar	624	3	10	Turkey	479	3
Sub-total		12,770	71	**Sub-total**		11,947	68
Other countries		5,274	29	**Other countries**		5,578	32
Total		18,044	100	**Total**		17,526	100

Figure 2.5 illustrates the countries that contributed to the total number of Saudi tourists in 2019. Tourists from these countries accounted for 80 percent of all tourist arrivals to Saudi Arabia.

Figure 2.5. Saudi's top tourism markets as the total number of tourists, 2019

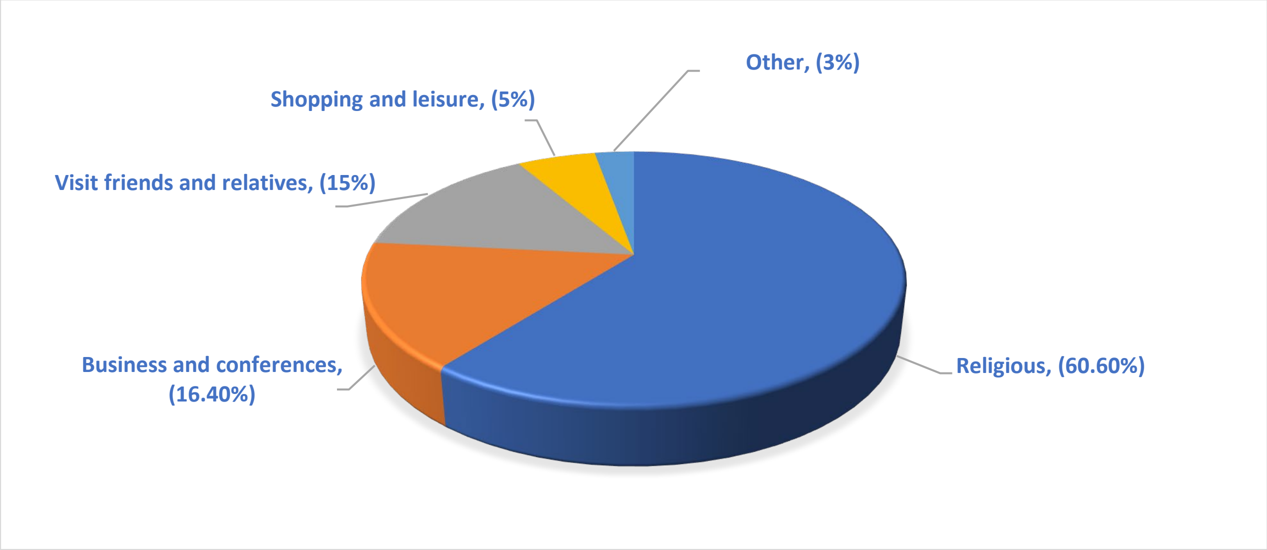


Source: Calculated from Saudi Tourism Information and Research Centre data (MAS, 2019)

Saudi tourism growth has been driven by three main demands: pilgrims, business, and VFR (Damanhouri, 2017). Most tourist arrivals to Saudi Arabia for religious purposes, accounting for around

61 percent of the total number of arrivals, followed by business visitors (16 percent), and VFR tourists (15 percent), as illustrated in Figure 2.6.

Figure 2.6. Tourist arrivals in Saudi Arabia according to the purpose of tourism, 2019

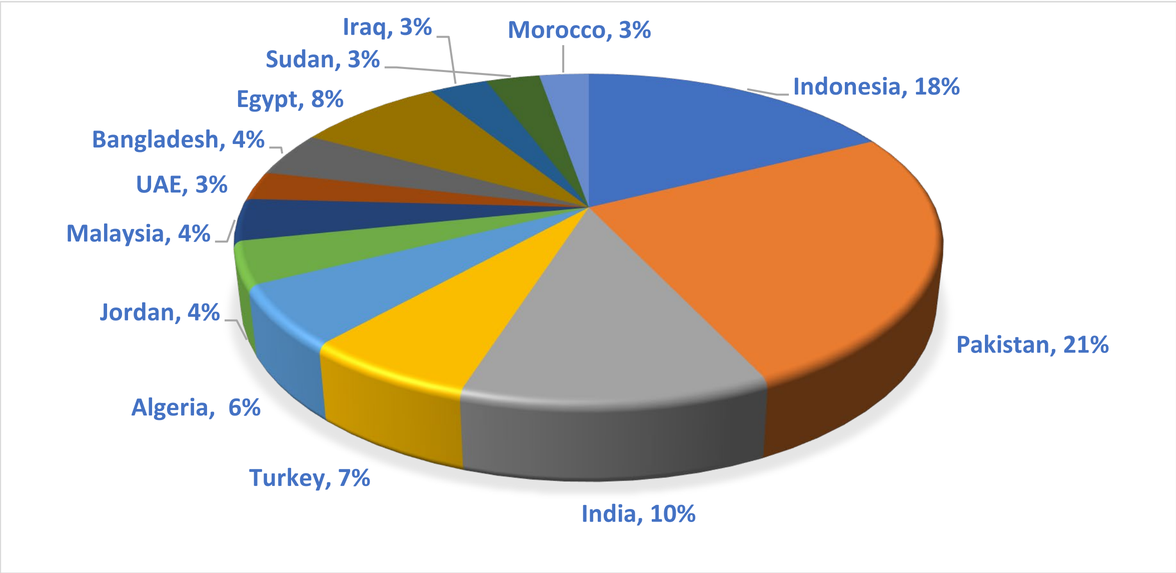


Source: Calculated from Saudi Tourism Information and Research Centre data (MAS, 2019)

2.3.2.1. Religious tourism

Figure 2.7 shows that more than 80 percent of religious tourist arrivals to Saudi Arabia came from Pakistan, Indonesia, India, Egypt, Turkey, Algeria, Bangladesh, Jordan, Malaysia, Iraq, and Sudan. Pakistan had the highest number of pilgrims to Mecca, followed by Indonesia and India. These countries are Muslim countries with a high percentage of Muslim populations.

Figure 2.7. Saudi's top tourism markets for religious purposes, 2019



Source: Calculated from Saudi tourism information and research centre (MAS, 2019)

Religious tourism was one of the earliest forms of tourism (Euchi et al., 2018; Sadi & Henderson, 2005). Over time, it has become a significant and segmented industry. Every year, nearly three million pilgrims travel to Mecca in Saudi Arabia to do Hajj. As noted in Chapter one, this is a compulsory religious obligation for adult Muslims and must be performed at least once in their lifetime if they are physically and financially able to undertake the journey (Henderson, 2011).

Religious tourism is the main reason for visiting Saudi Arabia since it is the unique destination for Hajj and Umrah (Stephenson, 2017). As previous mentioned Hajj can only be performed in a specific month each year (changing from year to year). For this reason, and in order to control the number of Hajj pilgrims, additional visa restrictions are applied during the Hajj, but not the Umrah. The e-visa launched in September 2019 is not applied for the purposes of the Hajj pilgrimage; it is only available for tourism and Umrah purposes. The Umrah Plus Program was launched in 2014, allowing Umrah pilgrims from 65 countries to stay in the country for one month to visit historical, heritage, and religious sites (Ekiz et al., 2017). Muslims who enter Al Masjid Al Haram (the Holy Mosque) and perform Umrah in Mecca can also visit the Medina, the second holiest place for Muslims after Mecca. This has many religious tourist attractions including Al-Masjid a Nabawi and the grave of the Prophet Muhammad (Ibrahim et al., 2021). It is common for Muslim pilgrims to travel between Mecca and Madinah in the same tourist package. Consequently, Al-Masjid Al Nabawi is one of the most desired attractions for Muslim pilgrims during Hajj and Umrah.

Religious tourists are the biggest spenders in Saudi Arabia compared to other types of tourists and provide benefits to the Saudi economy (Fourie et al., 2015). Pilgrim expenditure includes entrance and visa fees, external and internal transportation, food and drink, accommodation. The Hajj and Umrah pilgrimages contribute an estimated USD 12 billion annually to Saudi Arabia's GDP, representing 20 percent of the country's non-oil GDP and seven percent of total GDP (Alam, 2021).

The number of pilgrims visiting Mecca to fulfil their religious requirements has increased significantly since the mid-1950s when it was less than 100,000 (Bianchi, 2004). According to the GaStat (2021b), pilgrim numbers reached 1,357,240 in 2000 and over three million in 2019. Umrah pilgrims reached 19,158,031 in 2019, including 7,457,663 who came from outside the kingdom, and 11,700,368 domestic pilgrims. The number of religious tourists has increased as long-haul travel has become faster, safer, and more affordable due to low-cost carriers in the Gulf region, especially in Saudi Arabia (Alsumairi & Tsui, 2017). This means that while pilgrims travel to Mecca and Madinah primarily for religious obligations, their visits are influenced by other factors such as infrastructure, safety, security, the quality of health care and the quality of essential services (Ladki & Mazeh, 2017). As the elderly represent a large segment of pilgrims, they need health care and housing services in the two holy cities, provision of food facilities to reduce food risks and prevent food poisoning, and good water quality. In 2013, for example, 87 percent of Hajj pilgrims were elderly (>65 years old), with 83 percent facing a significant risk of health problems (Rustika et al., 2020). Saudi Arabia's Ministry of Health has a critical responsibility during the Hajj season to provide effective health care for pilgrims, by developing health facilities and assigning trained health personnel (Nafea, 2017).

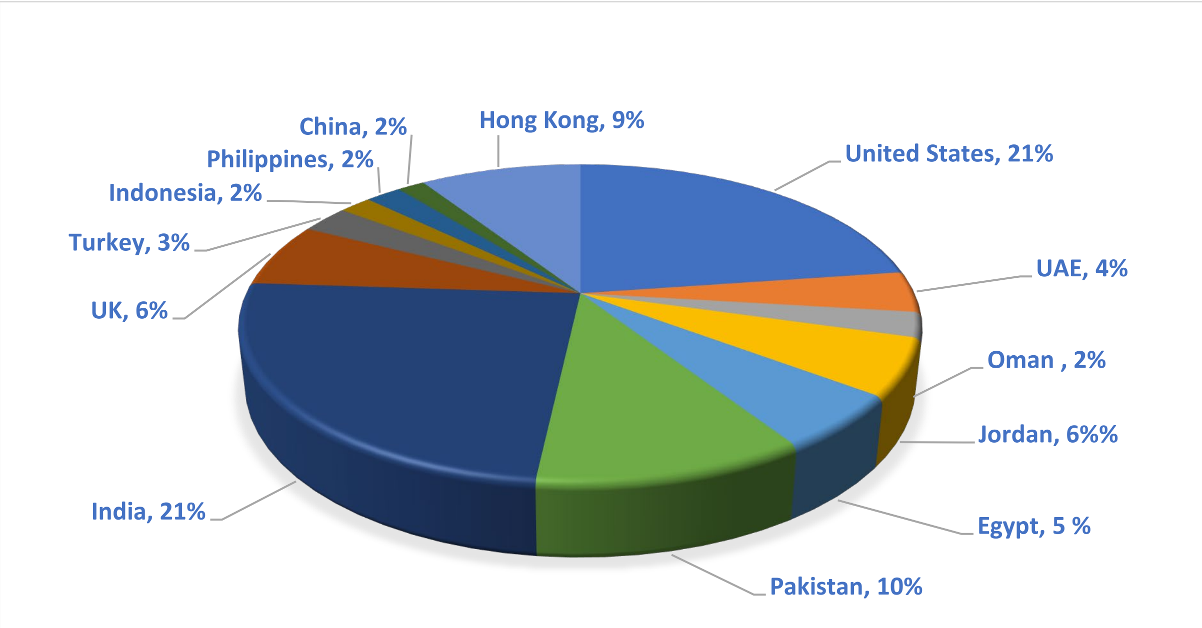
The development of education in Saudi Arabia has assisted the improvement of human capital and services, including knowledge of more languages to talk to tourists and ease communication with pilgrims. Innovation and entrepreneurial management of the Hajj and Umrah are likely to contribute to the development of services, accommodation and housing, and investing in security and safety technologies, retail trade, catering, logistics, information and translation services, as well as other services provided to pilgrims.

The Vision 2030 project aims to increase the number of international religious tourists to 30 million by 2030 (Nhamo et al., 2020).

2.3.2.2. Business tourism

Business tourism is often referred to as business events or meetings, incentives, conferences and exhibitions (MICE). Figure 2.8 shows the countries that made up Saudi Arabia's business tourism markets in 2019. The economic and political relationships between Saudi Arabia and these countries are crucial to ensuring continued business tourist arrivals.

Figure 2.8. Saudi's top tourism markets for business purposes, 2019



Source: Calculated from Saudi Tourism Information and Research Centre data (MAS, 2019)

Saudi Arabia's business tourism sector has grown significantly in recent years. In 2009, just nine percent of all tourists to Saudi Arabia arrived for business purposes, but by 2016 that number had climbed to

12 percent and then to 16 percent in 2018. Business visitors have a higher purchasing power than other tourists and are likely to spend more money while they are in their destination.

The Saudi Exhibition and Convention Bureau was established in 2013 to develop and organise business tourism. The objective of this organisation is to promote the Saudi Arabian conference and exhibition industry so that it effectively contributes to the kingdom's economic growth (Monshi & Scott, 2016). It controls the licencing and growth of many business sectors, including events and venues. In December 2018, the Saudi Conventions and Exhibitions General Authority was established with the objective of further developing the exhibitions and conventions sector in accordance with international best practices. This would enhance its economic contribution, increase its effectiveness, and help overcome obstacles to its growth.

Saudi Arabia is located strategically between Europe, Africa, and Asia, making it an ideal destination for regional and international conferences and exhibitions. Several international airports and airlines operate regular flights in the country, providing excellent air connectivity.

Governments in Saudi Arabia are actively supporting the development of business tourism by providing various incentives to attract business travellers, such as visa facilitation, tax exemptions, and event funding, in addition to investing in developing tourism infrastructure, such as airports, roads, and hotels. As a result, Saudi Arabia is an attractive destination for business travel. Many business travellers also have the opportunity to combine their work trips with visits to historic sites, such as Mecca and Medina, thereby enjoying the country's rich cultural and religious heritage.

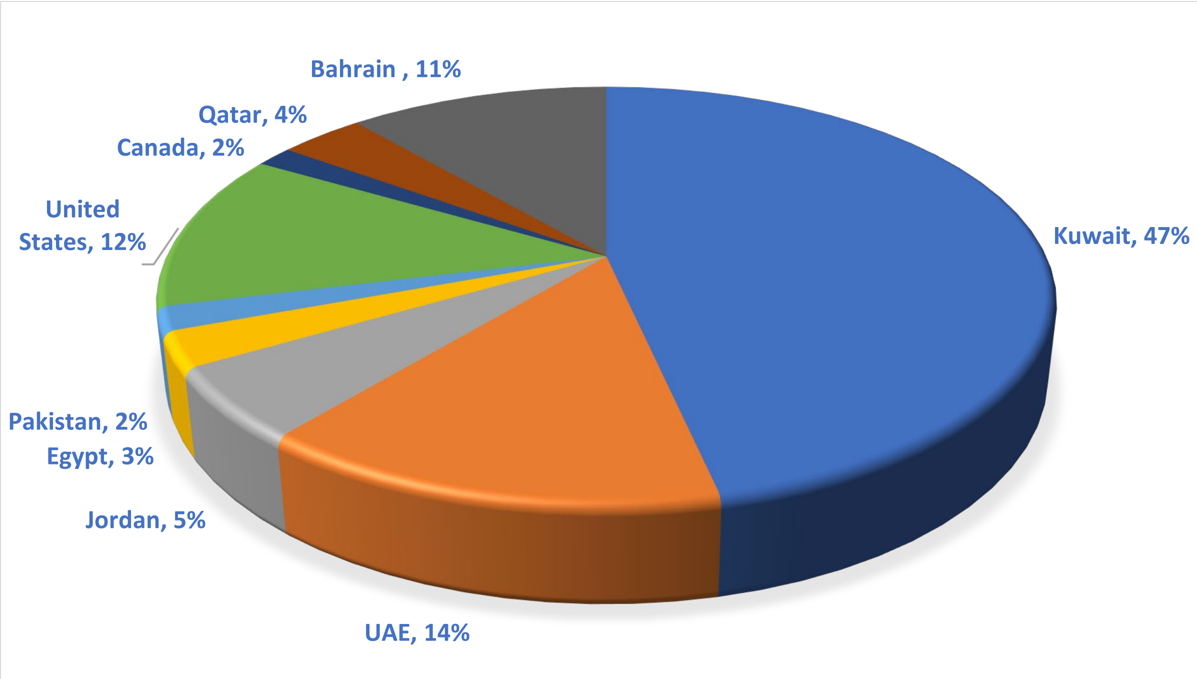
Business visitors account for more than 20 percent of all tourism spending in the kingdom (when pilgrimages to Hajj and Umrah or journeys to Madinah are excluded). More than 3.2 million visitors attend exhibitions and conferences every year, investing more than SR 6.8 billion or USD 1.81 billion (SCTA, 2014). The kingdom boasts over 600 exhibition, conference, and meeting facilities, and over 500 licenced exhibition and conference organisers (Khashan, 2017). The business tourism industry in Saudi Arabia has grown rapidly because of the country's economic and urban revival. Its business tourism is a major market since it is one of the largest economies in the Middle East, attracting significant foreign investment in various sectors, including energy, infrastructure, and technology.

Various factors have contributed to the growth of business tourism in Saudi Arabia. As noted above, the Saudi Arabian government has supported tourism development by investing in better infrastructure (Damanhouri, 2017). This includes building high-quality hotels in strategic locations and creating experience in hosting large numbers of tourists. A key element of the kingdom’s business tourism investment is the Abraj Kudai, the world's largest hotel, with a ring of 12 towers (each 45 storeys high), 70 restaurants, 10,000 guestrooms, and multiple roof helipads, at a cost of billions (Smith, 2016). Other factors contributing to business tourism growth include the availability of establishments and support services, as well as the rising private sector that focuses on the business tourism market (Mair, 2012).

2.3.2.3. VFR tourism

VFR is the third motivator for travelling to Saudi Arabia after religious and business travel (Ekiz & Oter, 2017). The top countries that engage in VFR tourism are Kuwait, UAE, Bahrain, Jordan, Qatar, Egypt, and Pakistan. Figure 2.9 shows that these countries make up 90 percent of all VFR visitors. Kuwait and the UAE are the two most important sources of VFR tourists, as neighbouring countries only a short distance from Saudi Arabia. These countries share the same language, religion, and economic structure as Saudi Arabia. Kuwait, UAE, Bahrain countries have family and friends living in Saudi Arabia. Moreover, many foreign workers in Saudi Arabia come from countries like Jordan, Pakistan, and Egypt, and their families and friends visit them. In addition, Arab countries such as Egypt and Jordan also have a strong cultural and historical connections with Saudi Arabia and also have workers in Saudi. Thus, many Egyptians and Jordanians travel to Saudi Arabia for VFR purposes.

Figure 2.9. Saudi's top tourism markets for VFR purposes, 2019



Source: Calculated from Saudi Tourism Information and Research Centre data (MAS, 2019)

There is a rich cultural heritage in Saudi Arabia and stunning natural landscapes that are attracting tourists from all over the world, leading to an increase in tourism. In addition to religious tourism, the Saudi government is actively promoting VFR tourism. In Saudi Arabia, Riyadh, Jeddah, and Dammam are popular destinations for VFR tourism since they are homes to many museums, traditional markets, and archaeological sites. Additionally, tourists can explore the stunning Red Sea coast, the majestic mountains, and the vast deserts of Saudi Arabia.

2.3.3. Identifying key challenges to tourism development

Challenges facing tourism in Saudi Arabia can be summarised as follows:

- Travel to Saudi Arabia may be affected by regional tensions in Iraq, Syria, and Yemen. Political turmoil in the Middle East (Zamani-Farahani & Henderson, 2010). In the past Saudi was not concerned about political risk because it didn't affect religious tourism. However, now as the country is looking to grow its tourism market, such a risk does matter.
- Due to the low cost of car ownership and cheap oil supplies, Saudi citizens are able to use their own cars for transportation. However, efficient public transportation is essential for tourism. In order to increase the arrival of independent tourists, airports, maritime ports, bus terminals, and train stations must be connected to city centers and other cities by frequent and visitor-friendly transport solutions.
- The workforce primarily determines tourism success. Employees are considered internal customers. Customer satisfaction is strongly influenced by service quality, which is deeply shaped by labor quality. Saudi Arabia is overly dependent on foreign workers, which can negatively affect tourists' perception of authenticity when receiving service from non-Saudi employees. In order to ensure a long-term sustainable tourism industry in Saudi Arabia, it is imperative that Saudi Arabia educates a considerable number of its young generation to work in the tourism industry. Tourism, like many other service industries, can contribute to the reduction of unemployment in the country.
- The primary economic challenge for Saudi Arabia remains the volatility of oil prices, which is the primary source of revenue for the country, allowing it to develop new leisure and entertainment projects and destinations. The tourism sector's future is uncertain and contingent on the continued flow of investments generated by oil revenue, public and private sector engagement, and FDI.
- Although Saudi Arabia attracts a very loyal segment of tourists as religious pilgrims, understanding changing global traveler profiles is essential if other segments of the tourist market are to be attracted. It is necessary to prepare human resources, create infrastructure, and change mindsets to develop responsible tourism, ecotourism, and other visitor and nature-friendly tourism approaches. The importance of solutions for green, sustainable tourism cannot be overstated.
- Saudi tourism infrastructure is rapidly improving. However, this must go beyond the construction of hotels by international chains. It is important for local authorities and municipalities to enhance service standards and the standards of supporting firms in the tourism

industry. Various tourism-related businesses, including oil stations, retail markets, automobile tourism, as well as facilities for the elderly, and other related businesses, must be designed.

- Water shortages and excessive heat in Saudi Arabia can create sanitary problems such as diseases. Climate issues create challenges for children, the disabled, the elderly and sick tourists. Seasonality can be observed for some Saudi destinations, but for religious tourism seasonality is an outcome of calendar arrangements. Sustainable tourism practices need to be adopted but this has a price and timespan.
- Generally, religious tourism is concentrated in three cities, Mecca, Medina, and Jeddah, and this may create congestion if not well planned.
- Saudi Arabia faces competition from its neighboring countries. Across the Red Sea lies Egypt, where the coast is dotted with large, established beach resorts, such as Sharm el-Sheikh. Tourism in Egypt has been operating for decades and has the advantage of lower prices and relaxed social regulations. Jordan has been a popular tourist destination due to the attractions of such places as Petra and Wadi Rum. The UAE is investing heavily in the hospitality sector as part of its endeavors to wean itself off its economic reliance on fossil fuels.
- Aspects of Islamic culture, such as prohibited alcohol consumption and strict dress codes, can present challenges for inbound tourism demand in Saudi Arabia. These cultural norms, rooted in religious beliefs and traditions, can significantly impact the preferences and expectations of international tourists.

2.3.4. Saudi Arabian tourism potential

Despite the challenges to Saudi Arabia tourism, there are many opportunities. These can be summarised as follows:

- Religious attractions in Saudi Arabia give the country a distinct identity as an Islamic tourist destination. It is a unique destination for Muslims worldwide (Bokhari, 2021). Muslims all over the world pray five times a day in the direction of Saudi Arabia's holy city, Mecca. Furthermore, millions of Muslims travel to Saudi Arabia each year to visit the Holy Mosques of Mecca and Madinah (either during Hajj or Umrah, as one of Islam's five pillars).
- Saudi Arabia has jumped ten places to 33rd in the 2021 World Economic Forum (WEF) Travel and Tourism Development Index. The index ranks 117 countries based on 17 aspects that are critical to the growth and resilience of their tourism and travel industry. Because of improvements in almost every indicator, Saudi Arabia moved from 43rd place in 2019 to 33rd by 2021. Saudi's significant improvement in this ranking is a result of considerable investment in the tourism sector, as well as its leadership in future-proofing the sector globally. Saudi Arabia brings together key players to build a better future for tourism by promoting sustainable and resilient development.

- Another significant strength of Saudi Arabian tourism is its geographical location in the Middle East (Al-Hazmia, 2020). It is at the intersection of Asia, Africa, and Europe, bounded on the west by the Red Sea and on the east by the Arabian Gulf (see Figure 2.10) (Bashir et al., 2020).

Figure 2.10. Map of Saudi Arabia

Source: Fanack (2020)

- One of the strongest aspects of Saudi tourism is the authenticity available through its wide range of cultural heritage (dress, food, drink, entertainment, etc.).
- In Saudi Arabia, tourism education has recently been introduced and colleges and universities are now offering diplomas and degrees to prepare the future local human resources for the industry.
- Additionally, in order to diversify the economy, the Saudi government has identified tourism as a key sector and has taken steps to support its development. As indicated throughout this chapter, these initiatives include simplifying visa processes, attracting foreign investment, and promoting cultural and natural attractions.
- One of the strengths of Saudi Arabian tourism is the country's strong economy and ability to support the development of the tourism sector. Saudi Arabia's economic viability is aided by its proximity to emerging markets including India, China, Turkey, and GCC member nations.
- Furthermore, Saudi Arabia has competitive tax legislation, as well as gasoline and energy supplies for foreign investors. Tourism in Saudi Arabia can benefit from energy consumption,

trade with India and China, and African and Asian development. Strong trade relations could boost business travel.

- Four mega projects have been established by Saudi Arabia authorities, designed to diversify the economic, social, and cultural directions of the kingdom (Mahate & Parahoo ,2023). 1) Qiddiyah Entertainment City will be the world's largest recreational and entertainment city. It will feature theme parks, entertainment centers, sports facilities to host international competitions, training academies, desert tracks for motorsports, water and snow-based leisure activities, a safari, and a combination of historical and cultural attractions. 2) NEOM is a USD 500 billion proposal to develop a future city on the Red Sea in the northwest of the kingdom, near the Egyptian and Jordanian borders. Innovation centers and vacation areas will be included in the ambitious NEOM project, which is based on cutting-edge and zero-carbon technology to create a desert megacity. 3) The Red Sea Project is a high-end travel and tourist venture that aims to showcase the Red Sea's abundant natural riches to the region's residents and visitors. 4) The Amala Resort is one of the most opulent resorts in the world, focused on health and well-being, as well as art and culture (Qablan, 2019).

  These four ambitious projects aim to boost the country's economy while also enhancing inhabitants' lives by offering access to world-class tourist and leisure destinations. Saudi is also developing other projects, including the modernisation of infrastructure, the rehabilitation of tourism and heritage sites, the upgrading of the accommodation sector and travel agencies and tourism services, the development of activities and events in tourist sites, and the development of tourism human resources.

- UNWTO opened its first Middle East regional office in Riyadh in May 2021. This assists the Middle East region in recovering its tourism sector, as well as supporting the growth of tourism development.
- The major reforms in relation to human rights could enhance Saudi Arabia's image. The reforms include socio-economic reforms and, in particular, the significant steps taken to advance women's rights and increase Saudi women's access to the job market. Expatriate workers were provided with new labor laws in March of 2021, enabling them to switch jobs without seeking employer approval. By changing the exit and re-entry visa system, employees were given greater flexibility to travel outside the kingdom without having to seek permission from their employers on each journey.
- Tourism development in Saudi Arabia is positively impacted by its stability in an uncertain region. Its stability comes from strong political relationships with global leaders. In addition to being a top oil producer, the country also maintains strong commercial and political ties with Arab and Muslim countries and the rest of the world (Mansfeld & Winckler, 2004).

- Saudi Arabia is an active member of international organisations such as the G20, Arab League, OPEC, and the Organization of Islamic Cooperation (OIC). In addition, the influx of global expats and knowledge also support dense commercial and political relationships. Information technology also contributes to developing a globally educated, globalized new generation. Saudi society is very urbanized and young. Scholarships provide young citizens with the opportunity to improve their educational level.
- A significant investment in aviation could lead to a rise in tourists to Saudi Arabia, and the country could be used as a potential international flight hub. Tourism development in the Middle East is an excellent example of how tourism and aviation can contribute to the growth of a country.
- The Saudi Arabian government is implementing a number of domestic speed train projects that will benefit the country's tourism industries, including boosting domestic tourism and improving transportation for Hajj and Umrah.

2.4. COVID-19 impact.

Tourism is one of the most sensitive industries to crises such as wars, terrorist attacks, natural disasters, health risk pandemics and other unexpected events (Danbatta & Varol, 2021; Dube, 2022; Kocak et al., 2022). Recently, the COVID-19 pandemic has become the world's primary challenge, one of the biggest ever faced by international tourism demand. The market and supply chain faced huge challenges due to border closures and lockdowns imposed by several nations in response to the assumption that COVID-19 could be transmitted by tourists (Armutlu et al., 2021).

2.4.1. The impact of COVID-19 on global tourism demand

Prior to the emergence of COVID-19, the tourism industry became one of the most important industries in an increasingly interconnected global economy. It contributed approximately 10 percent of the world's GDP and 320 million employees globally. Additionally, the tourism industry stimulated economic activity via its multiplier effects on related economic sectors (Okafor & Yan, 2022; Okafor, Khalid, & Burzynska, 2021). After the virus emerged in China in December 2019 the cases rapidly increased and began spreading between countries and regions by March 2020 (WHO, 2020). The world has not experienced a pandemic of this magnitude in the last century (Orîndaru et al., 2021).

On 11 March 2020, the World Health Organization (WHO) declared COVID-19 a global pandemic. As a result, the organisation enforced several preventive measures in all countries to prevent the spread of the virus. The pandemic's massive and deep effect has generated unprecedented economic, social, and health challenges as a result of its cumulative effects in terms of global reach, and unprecedented measures taken by governments to contain it. As the number of COVID-19 cases increased, several governments shut their borders, restricting the mobility of their citizens. Travel agencies and tour operators ceased operations, airlines suspended flights, hotels, entertainment complexes, and restaurants closed, and sporting events were cancelled (Assaf & Scuderi, 2020; Kocak et al., 2022).

According to the UNWTO (2022), 2020 marked the worst year on record for tourism, with the number of international tourists decreasing by 74 percent compared to the pre-pandemic period, from 1.46 billion arrivals in 2019 to 381 million arrivals in 2020. International tourist numbers decreased by 82 percent in Asia, 73 percent in the Middle East, 69 percent in Africa, 68 percent in Europe, and 68 percent in the US. The decline in international tourism in 2020 likely lead to a loss of around 1 billion international arrivals and USD 1.1 billion in international tourist revenues. Ultimately, the fall in international tourism caused by the COVID-19 pandemic was predicted to result in a global GDP decline of more than two percent in 2020 (UNWTO, 2020). The total contribution of travel and tourism to GDP was 8.9 percent of the total economy in 2019, but only 4.9 percent in 2020. The total contribution of travel and tourism to employment in 2019 was 6.88 million jobs (8.9 percent of total employment), but in 2020 it was 5.69 million jobs (7.7 percent of total employment).

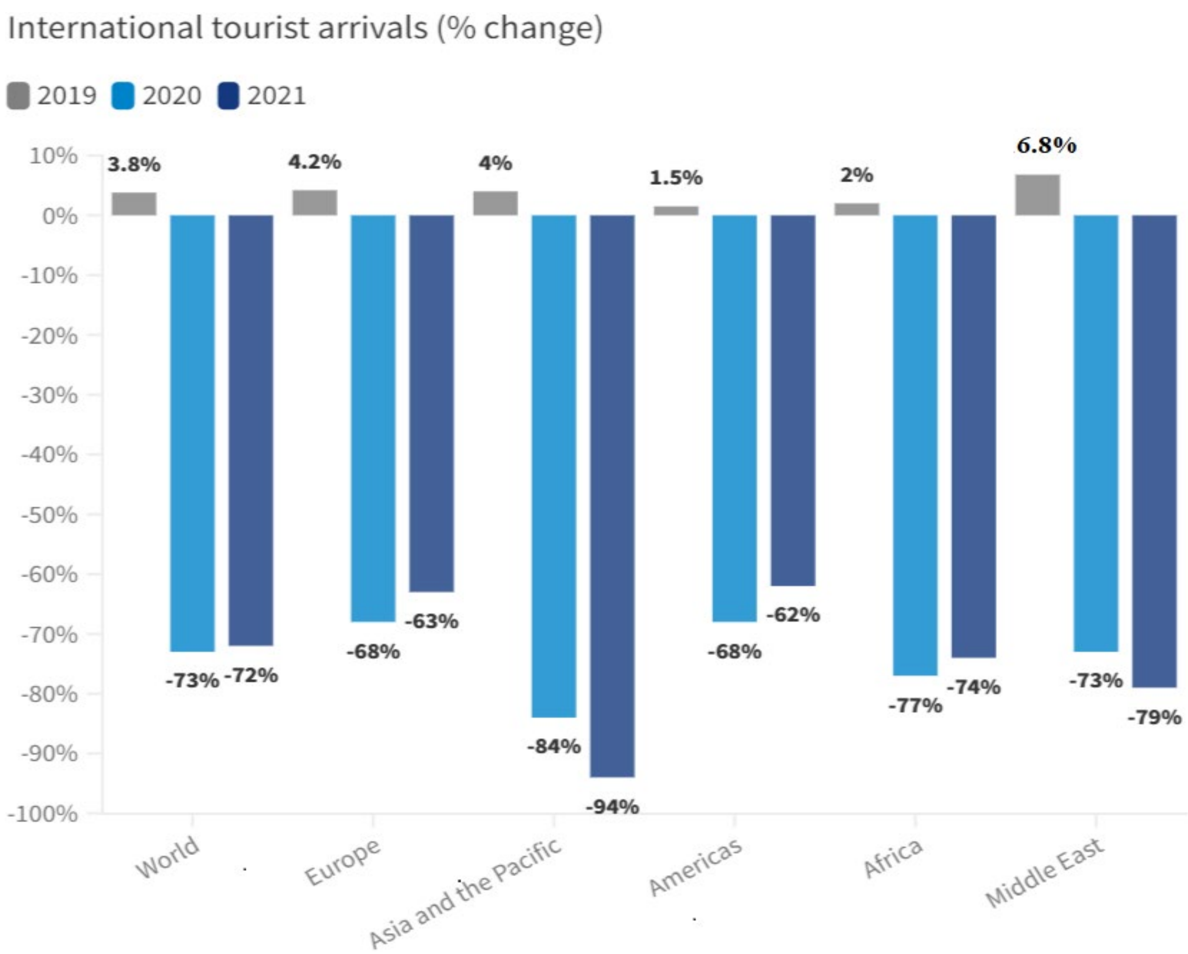
The annual report of the WTTC (2021a) revealed that the travel and tourism industry lost about USD 4.5 trillion, reaching USD 4.7 trillion in 2020, a shocking 49.1 percent lower GDP than in 2019; comparable to the world economy's 3.7 percent decrease in 2020. In 2019, the travel and tourism industry contributed 10.4 percent to world GDP, falling to approximately 5.5 percent in 2020, and 62 million jobs were lost in 2020, a loss of 18.5 percent. This 18.5 percent drop was noticed across the whole tourism and travel sector, particularly among small and medium-sized enterprises, which account for 80 percent of all worldwide businesses in the sector and were the most impacted. Women, minorities, and youth have been disproportionately impacted by the pandemic (Diakonidze, 2021).

According to UNWTO reports in 2021, global tourism increased by four percent compared to the previous year (415 million versus 400 million). However, according to preliminary UNWTO reports, as can be seen in Figure 2.11, international tourist arrival numbers (overnight visitors) were still 72 percent lower than in the pre-pandemic year of 2019. This follows from 2020, which was the worst year in history for tourism, with international arrivals dropping by 73 percent.

To get back to pre-COVID-19 levels, tourists must feel safe to travel. The COVID-19 vaccination has been playing an integral role in reviving the tourism industry. Since the middle of 2021 the WHO has approved 22 vaccines. More than 5.18 billion people worldwide have received a dose of the COVID vaccine (as of May 2022), equal to about 67 percent of the world population. Due to differing degrees of mobility restrictions, vaccination rates, and traveller confidence, the pace of recovery remained slow and unequal across the globe. Europe and the Americas had the best results in 2021 compared to 2020 (+19 percent and +17 percent, respectively), but they were still 63 percent below pre-pandemic levels.

Africa had a 12 percent increase in arrivals in 2021 compared to 2020, although this is still 74 percent lower than in 2019. Arrivals in the Middle East fell by 24 percent compared to 2020 and 79 percent compared to 2019. Arrivals in Asia-Pacific were 65 percent lower than in 2020 and 94 percent lower than pre-pandemic levels, because many destinations remained closed to non-essential travel. According to the first issue of the UNWTO World Tourism Barometer for 2022, growing vaccination rates, together with relaxing travel restrictions due to increased cross-border cooperation and protocols, have all contributed to the release of pent-up demand. International tourism recovered moderately in the second half of 2021, with international arrivals down 62 percent in both the third and fourth quarters of 2021 when compared to pre-pandemic levels. According to limited data, international arrivals in December were 65 percent lower than in 2019.

Figure 2.11. International tourist arrivals (% change) during the COVID-19 period, 2019, 2020 and 2021.



Source: UNWTO (2022)

2.4.2. The impact of COVID-19 on Saudi tourism demand

As Saudi Arabia has been working to improve its competitiveness to attract international visitors as part of its Vision 2030 strategy, the number of tourist arrivals was expected to increase dramatically in 2020 and 2021. However, just a few months after opening its doors to tourists using the new electronic visa (non-religious tourism) (Alrefaei et al., 2022), the outbreak of COVID-19 closed the doors and any visas issued for tourism were cancelled. Borders were closed at the beginning of March 2020 and all flights from and to Saudi Arabia were suspended (Parveen, 2020). The new tourist industry experienced a loss in income and employment as a result of the COVID-19 pandemic (Ahmed & Memish, 2020).

Saudi Arabia implemented an impressive strategy for containing the spread of COVID-19 through a range of timely and well-developed initiatives, including quarantine, curfew measures, and mandatory face masks in all public settings. Significant investment in the healthcare sector assisted in the facilitation of the detection, tracing, and isolation of cases. Figure 2.12 shows a timeline of Saudi Arabia's response to COVID-19 at the national level.

Figure 2.12. The response of Saudi Arabia to the COVID-19 pandemic regarding Hajj and Umrah

Source: The American Journal of Tropical Medicine and Hygiene 104, 3; 10.4269/ajtmh.20-1563

Religious tourism, the biggest tourism market in Saudi Arabia, was seriously affected. Saudi Arabia's response to the COVID-19 outbreak was critical for the safety of Hajj pilgrims. On 27 February 2020, international entry for Muslims seeking to undertake Umrah was cancelled. Umrah rituals were banned on 4 March 2020, just two days after the first COVID-19 case was detected in Saudi Arabia. On 23 March 2020, Saudi Arabia banned international flights. To further combat the COVID-19 pandemic, on 17 March 2020, the Saudi government announced the suspension of daily and Friday prayers in the two great mosques of Mecca and Medina, as well as in other mosques throughout the country. Only mosque staff and imams were permitted admission, with explicit instructions to adhere to infection prevention and control measures. These actions were implemented even though the country had fewer than 300 cases. This early response aided Saudi Arabia in reducing the virus' spread. On 22 June 2020, the Saudi government declared that the 2020 Hajj pilgrimage would take place, but only for a limited number of Saudi Arabian pilgrim citizens and residents, with numbers not exceeding 10,000 at the time. In 2021, only 60,000 citizens and residents (fully vaccinated) were allowed to do the Hajj.

COVID-19 restrictions and the suspension of pilgrimages for Hajj and Umrah led to economic losses for Saudi Arabia. Additionally, the intervention had a negative effect on revenue for the whole tourism value chain, from airlines to travel agents, hotels, restaurants, and local guides that rely on these mega-pilgrimage events for a living. To reduce the impact of COVID-19, the Saudi government implemented many assistance and recovery measures. To support the tourism sector, the Saudi government offered SR 9 million (USD 2.4 billion) to support salaries in the private sector, including travel and tourism. Moreover, the government committed to pay 60 percent of salaries for three months to keep companies from laying off employees. This was part of a plan that covered up to 70 percent of Saudi workers in the most affected companies and 50 percent of those in the least affected companies. More than 90,000 companies and 480,000 Saudi citizens had benefited from financial assistance as of July 2020 (OECD, 2020). In June 2020, the Saudi government announced a new tourism development fund with an initial capital of SR 15 billion (roughly USD 4 billion) to invest in the tourism industry and provide advice and financing to businesses that work in or are related to the Saudi tourism sector (TDF, 2020).

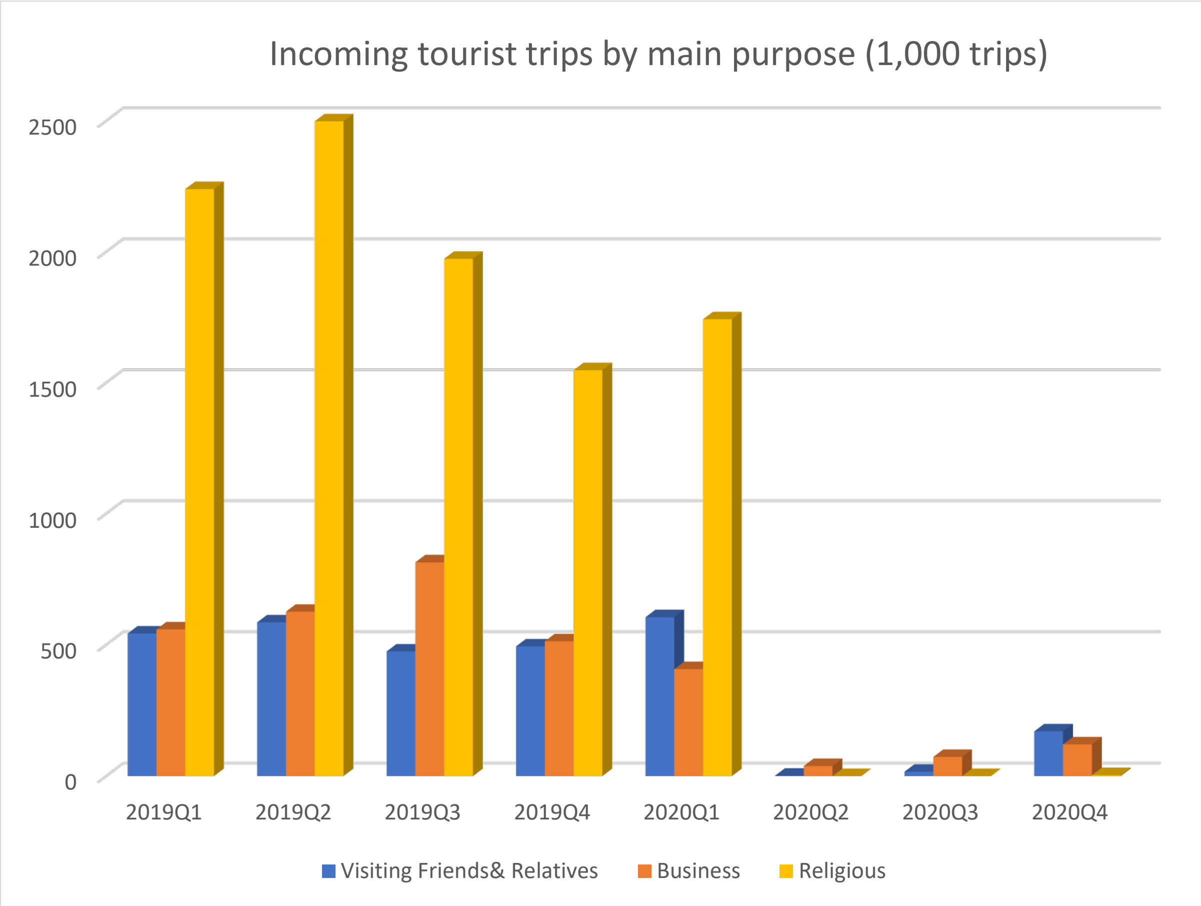
The Saudi government also suspended its new e-visa program for international non-religious tourists (Alam, 2021). Further, Saudis were prohibited from travelling to impacted nations and land crossings with the UAE, Bahrain, Kuwait, and Jordan were closed.

Due to vaccinations and preventative measures, the spread of COVID-19 has reduced since the middle of 2021. Figure 2.13 shows the number of COVID-19 cases in Saudi Arabia from March 2020 to September 2021. It is evident that the peak number of COVID-19 cases coincided with the period of border closures.

Figure 2.13. Confirmed COVID-19 cases (per million people) in Saudi Arabia

Source: COVID-19 Data Repository by the Centre for Systems Science and Engineering (CSSE) at Johns Hopkins University. https://github.com/CSSEGISandData/COVID-19

Figure 2.14. Saudi inbound trips by main purpose of visit (1,000 trips) fin 2019 and 2020.



Source: Ministry of Tourism

Inbound tourism trips for the three purposes of visit (religious, business and VFR) decreased sharply from March 2020 (see Figure 2.14). Religious tourism was most impacted by COVID-19 restrictions due to the potential risks associated with the normally large crowds participating in Hajj and Umrah. VFR tourism was also affected by COVID-19 restrictions, with slightly less impact than that on religious tourism. Business tourism was impacted the least, as business visits did continue in quarter 2 and 3 between April and September of 2020.

Between July 2021 and June 2022, 25,082,132 people in Saudi Arabia were fully vaccinated against COVID-19, representing 73.3 percent of the population. Saudi Arabia's health authorities declared that a booster dose would be required to maintain full immunisation status. Saudi Arabia has required a booster dose for all nationals travelling outbound of the kingdom and inbound tourists since 9 February 2022. A booster dose is required for pilgrims participating in Umrah. From 14 February 2022, international pilgrims were required to receive booster shots before entering Saudi Arabia for Umrah. Vaccines effectively reduce mortality rates and the severity of disease (Paltiel et al., 2021).

It was understood that countries with higher vaccination rates had a greater chance of reopening borders and returning to normal business operations, allowing social and economic activities to resume without the need for strict lockdowns. Dube (2022) argues that the tourist industry will continue to expand and recover, supported by the global vaccination programs currently in place.

On Friday 30 July 2021, the Saudi government announced that it would reopen its borders to fully vaccinated foreign tourists after a 17-month closure. The country left the suspension of entry for tourist visa holders, starting from 1 August 2021. Travellers fully vaccinated with Saudi-approved jabs would be able to enter the kingdom without the need for an institutional quarantine period. Saudi Arabia has further relaxed travel restrictions for visitors who have been vaccinated against COVID-19. Vaccinated tourists are no longer required to take a PCR or antigen test, either before departure or on arrival (Skirka, 2022). A chief executive officer of the STA revealed at the 2022 Arabian Travel Market, which took place in May 2022 at the Dubai World Trade Centre, that the kingdom received over 62 million domestic and international visitors over 12 months, representing a 72 percent recovery from pre-pandemic levels (Arabnews, 2022).

The Saudi Ministry of Hajj and Umrah announced on 9 April 2022 that one million domestic and international pilgrims would be permitted to participate in Hajj 2022, but with some restrictions. Each country was allowed a certain number of pilgrims, these pilgrims had to be under 65 years of age, be vaccinated as approved by the Saudi Ministry of Health and have a negative COVID-19 PCR test conducted within 72 hours of departure to Saudi Arabia. The Hajj dates for 2022 were 7-12 July (Saudiembassy, 2022).

2.5. Summary and conclusion

The international tourism industry is vital to the global economy, contributing significantly to GDP and employment. Despite several adverse events, the tourism industry is gradually expanding and contributing an increasing amount to GDP and employment. In terms of market share growth, Saudi Arabia's tourism sector out-performs those of other countries in the Middle Eastern region. Over the past few years, Saudi Arabia has made considerable efforts to diversify its economy away from oil. Previously, only individuals with business visas, religious pilgrims, and foreign workers were permitted to enter Saudi Arabia. The 2019 decision to release tourist visas was intended to positively impact the kingdom's tourism demand. In addition, the country has a long-term vision focused on expanding tourism and has made substantial investments toward this objective. As a result, Saudi Arabia will likely attract more tourists in the future. However, due to restrictions, curfews, stay-at-home policies, and quarantines imposed, the COVID-19 pandemic has shaken almost all industries, particularly the tourism sector, across the globe.

The next chapter focuses on reviewing the literature related to tourism forecasting and tourism demand modelling. It explores the factors that impact visitor flow to Saudi Arabia and discusses future planning and investment forecasting.

CHAPTER 3: LITERATURE REVIEW

3.1. Introduction

The main aim of this chapter is to review previous studies on modelling and forecasting international tourism demand and develop the research hypotheses. This chapter provides the set-theoretical and empirical basis for understanding tourism demand. The review of related economic theory and literature on tourism demand can act as a foundation for the econometric models employed in this thesis. The chapter is organised as follows: Section 3.2 outlines theories related to tourist demand and their explanatory determinants. Section 3.3 provides a brief review of international tourism demand determinants, followed by hypotheses development. Section 3.4 presents the recent literature on gravity models for tourism demand modelling and Section 3.5 presents the literature on the forecasting models used in previous studies. Section 3.6 concludes the chapter.

3.2. Theoretical frameworks for tourism demand models

The international tourism demand model is based on classical economic theory. Tourist income, tourism prices, substitute prices (prices of competing destinations), exchange rates, and transportation costs between the destination and the origin are considered explanatory variables of international tourism demand. Along with these independent variables, in the majority of studies, dummy variables have been used to examine the impacts of various events that are likely to affect tourism demand and to capture deterministic trends (Cho, 2010; Culiuc, 2014; Divisekera, 2003; Kadir & Karim, 2009; Peng et al., 2015; Shen et al., 2011). Income and prices have played a significant and key role in international tourism demand analysis, and Cho (2010) argued that this is not surprising given international tourism is considered a luxury commodity or service.

The primary objectives of tourism demand research have been to select the best tourism demand models, identify the major economic factors affecting tourism demand, calculate demand elasticities, and evaluate the models' forecasting powers (Song et al., 2012). Although economic theory dominates the tourism demand research, increasing attention is being given to the role of non-economic factors, as discussed in detail later in this chapter. Due to the difference between tourism products and other products and services, many researchers, as stated below, have concluded that proven economic theory is inadequate to fully explain the nature of tourism demand. Thus, incorporating both economic variables and important non-economic variables is expected to provide a clearer understanding of international tourism demand. The theoretical foundations for tourism demand models are primarily derived from consumer demand theory and the gravity model, which are all briefly discussed below.

3.2.1. Consumer demand theory

The economic theory, especially consumer demand theory, has been the basis of the majority of previous studies on international tourism demand. According to the consumer demand theory, demand is a function of price, income, transport costs, exchange rate, prices of substitute and /or complementary destinations and taste. The concept of tourism demand refers to the willingness and ability of consumers to purchase varying quantities of a tourism product at different price levels during any particular time in their income limit (Claveria, 2017; Lim, 1997a; Peng et al., 2014; Peng et al., 2015) . Tourism demand in the economic framework has been discussed in most of the tourism demand literature according to traditional economic theory (utility theory to analyse consumer behaviour). Economic theory states that the demand for a good or service is a function of its price, consumer income, substitute and /or complementary destination price, consumer preferences and tastes. The income of tourist demanders is the most important driver of tourism consumption. The more purchasing power potential tourists have, the greater the degree of tourism demand. Relative price is another variable that has a significant impact on tourism demand. Relative price impact is noticed mostly through relative exchange rates and the cost of goods and services demanded by tourists. Tourists are reasonably concerned about the expense of goods and services such as transportation, accommodation, cost of food, and cost of souvenirs.

The lower the overall levels of prices in the destination country, the higher the demand for tourism. With respect to the exchange rate, this measures the price variations between a destination country and the tourist's country of residence. International tourists' costs will be reduced if the domestic currency of the destination country reduces, known as ceteris paribus or all things being equal. Cheaper prices will most likely translate into either longer stays or greater visitor expenditure. It would also most likely result in a greater inflow of tourists as compared to those visiting other tourist destinations.

This theory could assist in explaining the tourism demand for a destination. Although income and prices play important roles in determining tourism demand, the factors affecting tourism demand are not limited by economic theory.

3.2.2. International trade theory

International trade is the exchange of goods and services among countries. This concept is one of the components of the invisible trade, that is, the services trade. Therefore, international trade theory aims to determine the reasons and motives for establishing trade exchanges and can be used to explain the reasons for the tourism flows between countries. This theory indicates that the international trade flows of services and goods are caused by supply-side factors. The significance of international trade was recognised early on by economists such as Adam Smith (1776) based on the theory of absolute advantage, and David Ricardo (1817), who developed comparative advantage theory. The comparative advantage theory proposes that a country will specialise in producing particular goods or services that can be produced at a lower marginal cost and opportunity cost than in other countries. The absolute advantage theory reflects the ability of a country to produce goods or services at a lower cost than can be achieved by other countries. In the tourism context, some countries have unique tourism resources that give them a monopoly, such as the pyramids in Egypt, the Taj Mahal in India, and the great wall in China (Burke & Resnick, 1991). The comparative advantage and absolute advantage theories include the benefits of freedom of international trade and the division of labour and privatisation.

To conclude, international trade theories focus heavily on supply-side factors, which is essential for tourism activity as it represent the destination's particular characteristics. However, tourism is a complex industry with several goods and services, and don’t allow to 'fully identify the supply side. International tourism is impacted not just by supply-side factors, demand-side factors also play a critical role. International trade theory was adopted by Algieri (2006), Keum (2010), and (Nosier, 2012). It can assist in understanding the patterns and trends of international tourism flow.

3.2.3. The gravity models.

The gravity model, which is based on Newton's law of gravitation, has been used widely in many studies dealing with patterns of international trade, migration, and FDI within countries. As tourism is also considered a form of trade in services, this model may be applied to the analysis of international tourism flows. Newton’s law of gravity in physics states that the attraction between two bodies is proportional to the product of their masses and inversely related to the distance between their respective centres of gravity. It has subsequently been adopted by economists to explain the movement of goods and factors between regions (Christie, 2002; Deluna Jr & Jeon, 2014; Isard, 1954), as well as the movement of visitors from a country of origin to a country of destination (Vietze, 2012).

The gravity model was applied by Pöyhönen (1963) and Tinbergen (1963) to argue that bilateral trade flows between countries can be explained by factors that capture import tendency and export potential, as well as forces that attract or inhibit bilateral trade. Increased economic size led to attracts countries to trade with each other. The income of both nations would positively impact export activity (Linnemann, 1966; Pöyhönen, 1963; Sandberg et al., 2006). In tourism demand, the income of the destination country reflects the economic development and ability to provide service and products to tourists and the income of tourism reflects their ability to travel overseas. Geographic distance indicators are a proxy for transaction costs. Linnemann (1966); Pöyhönen (1963) argued that greater geographical distance reduces flows because it increases travel costs.

Morley et al. (2014) provided a theoretical background for this model that showed gravity models for tourism could be derived from consumer choice theory. They argued the probability that a customer chooses a destination that is positively proportional to its attractiveness and inversely proportional to the distance to it. It is noted that in the base gravity model, the interpretation of tourism flows depends on three variables, represented by the size of the economy of the country under study, the economy size of the origin country (partner) expressed in the GDP per capita, and the geographic distance between them.

3.3. Determinants of international tourism demand

The dependent and in independent factors in tourism demand analysis are reviewed in the following sections.

3.3.1. Dependent variables

Three significant factors have traditionally been used to measure tourism demand in the tourism economics research. First is the number of international tourists (Altaf, 2021; Fung-Thai et al., 2015; Jong, 2020; Khalid et al., 2021b; Khalid et al., 2020; Kulendran & King, 1997; Martins et al., 2017; Okafor, Khalid, et al., 2021; Puah et al., 2018; Saayman & Saayman, 2004; Saha et al., 2017; Song et al., 2008; Song & Witt, 2012; Tanjung et al., 2017). Second is international tourism receipts (Sanchez-Rivero & Pulido-Fernández, 2020; Akal, 2004; Aslan, 2016; Cárdenas-García et al., 2015; Fung-Thai et al., 2015; Gholipour & Tajaddini, 2018, 2019; Shahzad et al., 2017; Song et al., 2010). Third is tourist nights/days spent in the destination country (Ferro Luzzi & Flückiger, 2003; Pagliara et al., 2017; Saluveer et al., 2020).

A literature review on the econometric modelling of tourism demand reveals that there is no widely accepted standard measurement of tourism volumes. None of the proxies listed above are entirely adequate as they do not cover all the aspects that characterise the demand for tourism in a particular location. Gonzalez and Moral (1995) pointed out that one of the primary challenges in analysing the potential of the tourism sector is to identify a specific indicator to measure external demand. Taking into consideration that the demand for tourism is a variable that is not directly observable and then measurable, it is essential to find an appropriate proxy to represent it.

As noted above, the number of international tourist arrivals is widely used as a proxy for tourism demand because it is considered the global tourism predictor and provides access to higher-frequency data. It is argued that tourist arrivals data is often up to date and issued on a reasonably prompt schedule (Wamboye et al., 2020). According to Shahzad et al. (2017), increased tourism arrivals imply increased expenditure and receipts. Crouch (1992) pointed out that approximately 70 percent of the studies that estimated tourism demand have used the number of tourists arrivals as the dependent variable, followed by tourist expenditure and/or receipts in about 49 percent of studies. Various studies have used total tourist arrivals as a proxy for tourism demand because of difficulties in obtaining data on tourism expenses and receipts (Altaf, 2021). Dogru et al. (2017) and Rosselló-Nadal and HE (2019) claimed that the selection of a particular dependent variable would completely depend on the analysis aim and whether destinations want to see an increase in the number of arrivals or expenditure.

3.3.2. Independent variables

The following sections review the economic factors, non-economic factors, and dummy variable factors that have been considered in tourism demand analysis.

3.4.2.1. The literature on economic factors

The independent economic variables adopted in this study are: income, relative tourism prices, travel cost, capital investment in travel and tourism, trade openness, and FDI.

Income

The economic theory of demand states that income is an important determinant of demand for tourism (Dwyer et al., 2010; Eilat & Einav, 2004; Witt & Witt, 1992). The increase in income leads to increases in the demand for all goods, which in turn increases the demand for tourism. Gravity models assume that destination country income (the exporting country) represents the country's supply and production capability to provide necessary services to visitors (such as shelter, food, transport, safety, and security), and origin country income (the importing country) reflects the high purchasing power capacity to travel. In general, the income of a destination can be considered an indicator of potential supply, whereas the income of the origin country can be seen as an indicator of potential demand (Linnemann, 1966). Tourism demand is expected to be positively related to the importing and exporting countries' incomes (Harb & Bassil, 2020a; Rosselló Nadal & Santana Gallego, 2022).

Most empirical studies show the income elasticity is higher than one, which means tourism is a luxury good and consumers are spending an increasing proportion of their income on international travel as income increases. Previous studies found the income factor has positive impact on tourism demand (Aki, 1998; Chin-Hong et al., 2014; Hanafiah & Harun, 2010; Jong et al., 2020; Peng et al., 2015; Lee et al., 2021; Proenca & Soukiazis, 2005; Tanjung et al., 2017; Xu & Dong, 2020; Kaplan & Aktas, 2016).

However, there are some interesting findings in prior studies regarding the impact of income on tourism demand. Firstly, a few studies, such as Fung-Thai et al. (2015), Y. Liu et al. (2018), and Sireeranhan et al. (2017), found that increasing tourist incomes lead to a decrease in tourism demand to the destination. The potential explanation for this was that if a tourist's income increases, they may be able to afford to visit another more luxurious destination. This is based on the theory of consumer behaviour. According to consumer behaviour theory, an increase in income up to a certain point will move customer demand to a higher level. In this case, when the income of the tourist increases, they might seek out an alternative destination. Other studies, such as Tatoglu and Gul (2019), found that destination income has a significant and negative effect on tourism demand. This may be due to the fact that the attraction capacity of destination countries, which is determined by their income, is a secondary predictor of tourist demand, and other factors may be more important to tourists than their income. Some previous studies found that the impact of income variables changes according to the purpose of visiting. For example, Gozgor et al. (2021) found income is not a significant factor for business trips and holidays. Similarly, Senadeerage (2020) found tourist income was not significant for business tourism demand. Norman (2004) and Rinschede (1992) argued that religious tourism was not impacted by income, while Shaheen (2019) found positive relationships between income of the country of origin and religious tourism.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis E_1: The income of destination and origin countries has a positive and significant impact on all tourism demand flow in Saudi Arabia.

Cost of living at the destination (tourism price)

Tourism demand modelling often considers three price factors: cost of living, travel costs, and substitute prices. As tourism involves the movement of people, both the costs of transport (the cost of travel in tourism) and the cost of living are necessary to ensure flow from country to country and should be included in a tourism demand model (Song & Lin, 2010). Economic theory states that if tourism prices in a destination country increase, tourist arrivals will decrease, ceteris paribus. The cost of living at the destination is referred to as the relative price (the relative cost of living in the destination country relative to the country of origin) (Albaladejo et al., 2016). According to Crouch (1992) and Lim (1997b), relative prices refer to the costs of products and services that tourists need to pay at a destination, including food and beverages, accommodation, shopping, local transportation, and entertainment. In some cases, alternative measures like destination competitiveness (e.g., the price competitiveness index) have been developed to address the limitations of using exchange rates as a proxy for price (Athanasopoulos et al., 2014; Etzo et al., 2014). It is important to note that the computation of such indices, including relative purchasing power parity (PPP) at the destination, account for factors like transportation costs, trade barriers, and market competition, which can lead to significant price differences across countries. Hence, demand models that incorporate cross-country data need to adjust for these factors. However, the consumer price index (CPI) has been recognised as a reliable measure of the cost of living and inflation at the destination (Assaf et al., 2019; Habibi & Abbasianejad, 2011; Song et al., 2019).

The destination country cost of living variable is affected by the exchange rate and therefore this needs to be taken into consideration. CPI adjusted by exchange rate (the CPI at the destination divided by the CPI of the tourist origin country, multiplied by the exchange rates between the country of origin and the destination country) is a widely used measurement of tourism price. Use of the exchange rate factor alone in a demand model may be very misleading and not an adequate proxy. A number of previous studies have used CPI adjusted by exchange rate to measure tourism price or the cost of living in the destination (Barman & Nath, 2019; Choong-Ki et al., 1996; Durbarry, 2008; Eilat & Einav, 2004;

Habibi, 2017; Habibi & Abbasianejad, 2011; Hassan & Meyer, 2022; Jackman & Greenidge, 2010; Kim & Lee, 2017; Vietze, 2012; Viljoen et al., 2019). When the cost of living in the destination increases, naturally tourists will consider tourism in the destination comparatively more expensive. This could be due either to the higher inflation rates of the destination compared to the origin countries or to the fact that the destination currency has become more expensive compared to the origin currency. However, Shaheen (2019) found that the price of tourism is positively related to the number of tourist arrivals for religious purposes. This study concluded that religious tourism is a 'Veblen good', that product demand increases as its price increases, and that the decision to take a religious journey is a reflection of financial capability and social status.

As noted earlier, the purpose of the visit may affect the type of response. For example, business tourists might be much less price-sensitive than leisure and holiday tourists. Kim and Lee (2017) found a significant effect between relative prices and exchange rates on inbound tourism. Holiday tourism is considered a luxury good with negative relative price elasticity, whereas business travellers are the least sensitive to relative price fluctuations. Tourists who are VFR are caught in the middle.

As Saudi Arabia is a unique destination for pilgrimage purposes, the substitute price was not considered. Other studies, such Heberling and Templeton (2009), and Shaheen (2019) also exclude substitution variables from their models.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis E_2: Cost of living at the destination (tourism price) has a negative impact on tourism demand flow in Saudi Arabia.

Travel cost

Travel cost is an important factor in tourism prices as it accounts for a large portion of international tourism costs (Crouch, 1994; Zaki, 2008). Additionally, it is theoretically and empirically reasonable to include travel costs in the demand model. Increased travel costs discourage international tourism demand for a destination (Altaf, 2021; Hanafiah & Harun, 2010; Jong et al., 2020; Kaplan & Aktas, 2016; Singagerda, 2020). Some studies have adopted a gravity model to measure travel costs by using the geographical distance between the capital cities of the origin and destination countries (Cho, 2010; Lorde et al., 2016; Malaj & Kapiki, 2016; Naudé & Saayman, 2005; Song & Witt, 2000; Xu & Dong, 2020; Xu et al., 2019; Yang & Wong, 2012). Greater distance between the country of origin and the country of destination leads to increased travel costs (cost of travel) and increased transportation time (Altaf, 2021; Hanafiah & Harun, 2010; Jong, 2020; Kaplan & Aktas, 2016; Morley et al., 2014; Singagerda, 2020). Other scholars have used oil prices as a travel cost proxy (Carson et al., 2011; Moore, 2010; Santana-Gallego et al., 2010; Shaheen, 2019; Wang, 2009). The effect of travel costs is often statistically significant and negative, which means that countries that are further away will incur higher transport costs and tourists will be less willing to travel to that destination. Some researchers have argued that international tourists prefer nearby destinations (Eilat & Einav, 2004; Fourie & Santana-Gallego, 2013; Kareem, 2008; Kumar & Kumar, 2019; Wang, 2009; Xu et al., 2019).

In contrast to these studies, Shaheen (2019) used oil price as a proxy for travel cost and found that increased international oil prices had a positive effect for a sample of higher-income countries (Kuwait, Qatar, and the UAE). This might be due to the fact that those countries have oil-dependent economies and any boost in the global price of oil might therefore be associated with increased tourism demand.

One drawback of using geographic distance as a proxy for travel cost is that it is time-invariant. On the other hand, using oil price as a proxy for travel cost does not reflect the distance between the two nations. As a result, Jong et al. (2020) measured the transportation cost by multiplying the geographic distance (in kilometres) by the crude oil price as a proxy for the cost of travel.

Travel costs may vary depending on purpose of the visit. For example, Dwyer et al. (2010) argued that leisure tourism seems to be more sensitive to price than business travel. This is because leisure tourism is based on discretionary expenditure, and many other goods and services (substitutes) compete for a share of the consumer's overall budget. Dwyer et al. (2010) also discussed numerous reasons why business travel is less price-sensitive than leisure travel, in fact, business tourists value their time more than leisure tourists do, they have fewer travel options, and the cost is often covered by the employer.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis E_3: Travel cost has a negative and significant impact on tourism demand flow in Saudi Arabia.

Capital investment in travel and tourism.

Capital investment in the tourism sector includes investments that are directly related to tourism, hospitality, and the transportation industry. Tourism growth relies heavily on investment in tourism (Paramati et al., 2018). Several studies have incorporated tourism infrastructure development factors as independent variables and found positive impact on tourism demand (Barman & Nath, 2019; Fourie & Santana-Gallego, 2013; Khadaroo & Seetanah, 2008; Muryani et al., 2020; Naudé & Saayman, 2005; Saayman et al., 2016; Triki, 2019; Viljoen et al., 2019; Yang et al., 2010). Jeje (2021) used a capital investment in travel and tourism factor in a study of tourism arrivals. This capital investment in travel and tourism is important for promoting economic growth and sustainability (Puah et al., 2018). Capital investment in the tourism sector in the destination country may stimulate government revenue, create job opportunities, promote infrastructure development, and, as a result, increase tourism (Paramati et al., 2018). These investments can be translated into the development of accommodation, restaurant and catering services, the establishment of affordable and reliable transportation services, catering services and improved tour guide operations, as well as other tourism-related investments (e.g., ICT, marketing logistics, and finance). Tourism serves as a significant source of employment opportunities and competent human resources are critical to the tourism industry’s development. According to Puah et al. (2018), human capital investment in the tourism sector is critical. Investors in the tourism industry have a responsibility to invest in the competency and well-being of their employees.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis E_4: Capital investment in tourism in the destination country has a positive impact on tourism demand flow in Saudi Arabia.

Trade openness

Trade openness is the primary determinant of inbound business tourism. Increasing trade flows between a country and its trading partners encourages more business travel. Therefore, a positive relationship can be expected between economic openness and demand for tourism. Intuitively, trade linkages could generate more business travel between countries. An open economy seems to be more likely to attract a larger volume of tourist demand than a country with comparatively less economic openness. Some studies have examined the relationship between international trade and tourism and found trade openness or volume of international trade has a positive impact on business tourism. This means business tourism is higher in countries with more international trade (Gholipour & Foroughi, 2020; Khan et al., 2005; Kulendran & Wilson, 2000a; Kulendran & Witt, 2003a; Smith & Toms, 1978; Tan & Tsui, 2017; Tsui et al., 2018; Turner & Witt, 2001; Wong & Tang, 2010). As higher international trade enhances an economy's capacity through increased capital investments, particularly in the tourism sector, it increases a country's tourism arrivals. Khan et al. (2005), and Kulendran and Wilson (2000b) found that business travel is more correlated with trade compared to holiday travel.

It is noteworthy that there have been studies at the aggregate level that have found a positive relationship between trade and tourism (Santana-Gallego et al., 2011; Shan & Wilson, 2001). Some critical aspects must be highlighted and taken into account in tourism demand modelling. The relationship between tourism and trade can be affected by a variety of factors such as the type of tourist, the origin country, the destination, and so on. Furthermore, Okafor et al. (2023) found that different income groups experience different effects of trade openness on tourism flows. For example, trade openness promotes tourism flows in low-income countries, whereas its effect is statistically insignificant in high-income countries.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis E_5: Trade openness has a positive impact on tourism demand flow in Saudi Arabia.

Foreign direct investment (FDI)

The OECD defines FDI as a type of cross-border investment made by a citizen (the direct investor) of a country with the intention of establishing a long-term interest, typically at least a 10 percent ownership interest in such a business operating in a country other than that of the direct investor (Mold, 2003).

FDI is a critical factor for providing resources to boost the tourism sector, such as infrastructure, capital, knowledge, distribution networks, and access to global marketing (Fauzel, 2020; Fauzel et al., 2017; Selvanathan et al., 2012; UNCTAD, 2007). It is also an essential factor in the transfer of product knowledge, skills and processes to the nations where foreign investors have a presence (Ayanwale, 2007; Blomström & Sjöholm, 1999). Furthermore, such foreign companies contribute significantly to human capital investment, particularly in training, which is crucial for tourism development. In addition, international hotel and restaurant chains with a strong reputation and a successful track record may lead to attracting more visitors (Tang et al., 2007).

The relationship between international tourism and FDI has been heavily debated in the empirical literature, with some studies arguing that FDI causes international tourism (Baier & Bergstrand, 2007; Tomohara, 2016), while others argue that international tourism causes FDI (Sanford Jr & Dong, 2000; Tang et al., 2007). However, there is evidence that international tourism and FDI cause each other (Arain et al., 2020; Fereidouni & Al-Mulali, 2014; Selvanathan et al., 2012). Endo (2006) assumes that many developing countries that are lacking resources and access to global marketing networks can compensate for their shortcomings through FDI. Alam et al. (2016), Aluko (2020), Fauzel (2020), and Gholipour and Foroughi (2019, 2020) have found that FDI has a positive and statistically significant impact on business travels. Yazdi et al. (2017) found no causation between tourist receipts and FDI. A rebound in investigative business and holiday travel could happen as a result of increasing FDI, creating a cyclical impact that boosts tourism (Tang et al., 2007). As a result, FDI was expected to have a positive impact on business tourism in this investigation. The government of Saudi Arabia has implemented strict regulations and guidelines to preserve the sanctity and integrity of the religious sites of Mecca and Medina. Therefore, there may be limitations on foreign investment in religious tourism, especially when it comes to direct involvement in managing or operating religious sites.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis E_6: FDI in the destination country has a positive impact on business tourism demand flow in Saudi Arabia.

3.4.2.2. The literature on non-economic factors

Several non-economic factors were found in the literature to be essential for explaining tourism demand. These are discussed briefly below with empirical evidence.

Human rights

Generally, tourists prefer to visit safe destinations. Some destinations are becoming increasingly dangerous to travel to because of political violence, crime, terrorism and several other factors. These factors increase the perception that a destination is a risky one. Even if such violent events are not directly related to tourists, they will likely exacerbate risk perception in these destinations. Research indicates a negative relationship between tourists' perceptions of risk or victimisation risk, and tourism demand for such destinations (Altindag, 2014; Cui et al., 2016; Llorca-Vivero, 2008). For example, Ghaderi et al. (2017) examined the relationship between collective security and tourism demand in developed and developing countries. At first, they examined the total security index. Subsequently, they classified the index into three subcategories (social security, economic security, and political security). Social security is associated with pressures on the population, such as population displacement, group grievances, human flight, and brain drain. Economic security relates to unequal economic development, poverty, and economic decline. Political security involves concepts related to the legitimacy of the state, the provision of public services, and security apparatus.

Hall (2010), and Pizam and Mansfeld (2006) argued that the lack of safety and security in tourist destinations led to substantial declines in global visitation are recorded. According to Ghaderi et al. (2017), physical security is no longer be the only issue in tourism destination security and safety, additional factors, including human rights, must also be addressed. When tourists feel unsafe, they may have a negative perception of the destination, resulting in fewer prospective tourists.

Fourie et al. (2020) and Saha et al. (2017) suggested that civil liberty reforms and increased freedom expands a country’s tourism industry. Saha et al. (2017) indicated that facilitating personal and civil freedom and safety from arbitrary persecution attracts international tourists to the country. Ghaderi et al. (2017), Hall and O’Sullivan (1996), and Lee et al. (2021) proposed that perceptions of political instability and violence, violent protests, social unrest, civil war, tourist events, perceived human rights violations, and other similar events can be seen as a threat to tourism for a variety of reasons: First, when there is political instability or violence in a country or region, it can create an atmosphere of fear and uncertainty, which can deter tourists from visiting. Tourists want to feel safe and secure when they travel, and if there is a risk of violence or unrest, they may choose to go somewhere else. Second, violent protests and social unrest can disrupt transportation and other infrastructure that tourists rely on, such as airports, roads, and public transportation. Third, civil wars and other types of armed conflicts can create a dangerous environment for tourists. Finally, tourist events can also be a target for violence and terrorism, which can create a perception of risk for tourists.

There is no universally accepted definition of human rights, but they are the basic standards without which people cannot live with dignity (Donnelly, 2013). The United Nations defines them as inherent in our nature as human beings, the foundation for the quality of life in which individual dignity and worth receives due respect and protection and as the foundation for freedom, justice and peace (UDHR, 1948). The Universal Declaration of Human Rights (UDHR) is the first universal statement on the basic principles of inalienable human rights, adopted in 1948 by the UN General Assembly without a dissenting vote and proclaimed as a common standard of achievement for all peoples and all nations. The UDHR is the foundation of international human rights law, and it sets out fundamental human rights to be universally protected.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_1: Enhancing human rights has a positive and significant impact of on tourism demand flow in Saudi Arabia.

Political risks

The tourism industry can easily deteriorate due to political and social unrest. As an example, the conflict in the Middle East and North Africa in 2011, as well as the rise in terrorism, have negatively impacted the international tourism industry (Saha & Yap, 2014). As a service industry, tourism is extremely sensitive to terrorism and political uncertainty. Conflict-free environments are indeed a necessity for tourism in any destination. However, the world has been challenged increasingly by terrorism and safety issues in recent years, and political risks have escalated globally, particularly in the Middle East region. Geopolitical risk factors and uncertainties (defined as the risk connected with wars, terrorist action, and tensions between nations that impair the regular and peaceful conduct of international relations) have been found to have a negative and significant impact on the tourism industry (Balli, Uddin, et al., 2019; Demiralay & Kilincarslan, 2019; Hailemariam & Ivanovski, 2021). Political risk has a negative influence on the supply and demand side of tourism in the industry (Ghalia et al., 2019). From the demand side, political risk creates a negative international image of a country (Ghalia et al., 2019; Kim et al., 2018). On the supply side, political risk can lead to delay in tourism investment and tourism related business activities (Ghalia et al., 2019; Saha & Yap, 2014).

A number of scholars have found that reducing political risk and improving safety quality can translate into significant economic gains for destination countries, helping to increase the number of tourist arrival (George, 2010; Ghaderi et al., 2017, 2019; Santana-Gallego and Fourie, 2020; Anbalagan & Lovelock, 2014; Asongu et al., 2019; Du Toit & Fourie, 2012; Fletcher & Morakabati, 2008; Gatsinzi & Donaldson, 2010; Kaynak & Marandu, 2006; Lepp & Gibson, 2003; Masinde & Buigut, 2018; Mohamed & Alseyoufi, 2018; Naudé & Saayman, 2005; Novelli et al., 2012). In general, a tourist's choice of a safe and secure destination depends on factors directly linked to security and peace (i.e., no civil unrest, crime, policy instabilities, terrorism, and regional conflicts). These factors affect the image and attractiveness of a destination (Mansfeld & Pizam, 2006; Seabra et al., 2013). Mansfeld and Pizam (2006) stated that tourists usually avoid areas with poor political stability and consider areas that would be less attractive for tourism but have better political stability. Eilat and Einav (2004), using the September 11 terrorist attacks as an example, argued that political risk is a significant factor in destination selection for both developed and developing countries.

Neumayer and Plümper (2016) examined the impact of terrorist attacks on Western tourists to Islamic countries. They found that terrorist attacks on a tourist destination in one country not only reduce tourist flow to the targeted destination but also to other similar countries and even flows from similar source countries to similar destination countries decline.

The Middle East has suffered the Arab Spring revolution and ongoing political instability (UNWTO, 2012). More specifically, Saudi Arabia has had many conflicts with neighbouring countries (Ekiz et al., 2017).

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis $\boldsymbol{D_2}$: Political risk has a negative impact on tourism demand flow in Saudi Arabia.

Global health risks

The growth of international tourist flows is a reflection of the rapid movement of large populations. This can lead to an increased risk of spreading communicable diseases impacts. In regard to the effects of disease on destinations, Past disease outbreaks, such as avian flu and SARS epidemics have had significant impact on tourism demand (Rosselló et al., 2017). For example, Wilder-Smith (2006) found travel to Asia-Pacific countries dropped by 12 million travellers as a result of the avian flu epidemic, and approximately three million people in the tourism industry lost their jobs following the SARS outbreak in China, Hong Kong, Vietnam, and Singapore, resulting in losses of more than USD20 billion (WTTC, 2003) ;(Zeng et al.,2005). The Foot and mouth disease had a significant impact on tourist expenditure in the UK (Blake et al., 2003). Blake et al. (2003) reported that foot and mouth illness reduced tourism spending, and Kuo et al. (2008) indicated that tourist arrivals in affected nations declined considerably. Tourism revenue in 2001 fell by almost £7.5 billion. McAleer et al. (2010) compared the impact of SARS on international tourist arrivals to Asia with human deaths resulting from avian flu. SARS had a greater impact on international tourist arrivals in both the short and long term than avian flu. The number of deaths related to SARS was clearly more important to international tourist arrivals than catching avian flu. During the swine flu outbreak, the UK tourism industry experienced significant negative effects in 14 major source markets. As a result of the swine flu outbreak, visitor arrivals from mainland China, Spain, South Korea, and Russia declined in greater amounts than those from the other source markets countries (Page et al., 2012). A number of researchers have found that COVID-19 and the restrictions associated with it have had a significant effect on the volume of global tourism (Altig et al., 2020; Aronica et al., 2022; Baum & Hai, 2020; Gallego & Font, 2020; Gössling et al., 2020; Hu & Lee, 2020; Muhammad et al., 2020; Yang et al., 2020). In addition, Nasir et al. (2020)

and Prasetio et al. (2022) found that COVID-19 reduced the number of religious tourism visitors to Sunan Giri Tomb and Iraq, which negatively affected the socio-economic conditions of the surrounding community. Theos' studies have used dummy variables to capture the effect different disease outbreaks, such Cheng (2012) and Viljoen et al. (2019).

However, recent studies in tourism demand, including Karabulut et al. (2020) and Ghosh (2020), have used a newly developed indicator known as the World Pandemic Uncertainty Index (WUPI). This was developed by Ahir et al. (2020) to investigate the effect of pandemic uncertainties and global pandemics on tourism demand. Before 2020, there were no indexes to measure the uncertainty caused by pandemics. The emergence of major concerns and the worldwide uncertainty caused by COVID-19 led to the development of this new index. The data included in the WUPI encompasses all of the pandemics that have occurred since 1996.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_3: Global health risk has a significant negative impact on tourism demand flow in Saudi Arabia.

The Hajj risk is a type of crisis in the Saudi Arabia context. The Hajj is the largest annual gathering in the world, with more than two million Muslims gathering in Mecca, the holiest city in the world (Qurashi, 2018). On 24 September 2015, at least 700 pilgrims died and 900 were injured due to overcrowding and a stampede. This event was a tragedy for Saudi Arabia and other involved nations (Idris, 2019; Naar, 2015). Naturally, this event was expected to negatively impact tourism demand for religious purposes. Previous studies have used dummy variables to capture the impact of a specific event on demand for tourism. For example, studies of tourism demand have included fictitious variables to capture the effects of oil crises, economic crises, political instability, or sporting and social events. Lee (2005) used the following dummy variables in examining tourism demand: the first oil crisis, 1974-1975; the second oil crisis, 1979-1980; Beijing political accident June 1989 and 1990; the Gulf crisis, 1991. White (1985) used the 1968 rioting in France as a dummy variable; Veloce (2004) used the African boycott of the 1976 Montreal Summer Olympic Games; and Habibi et al. (2009) used the Asian finance crisis (1997) and SARS (2003).

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_4: The Hajj incident has had a negative and significant impact on religious tourism demand flow in Saudi Arabia.

The prosperity of the destination

The literature indicates the importance of tourism growth on country prosperity through creating more jobs and developing infrastructure, but the effect of the destination country's prosperity on tourism growth has yet to be researched. The prosperity of a destination country has a significant impact on tourism growth, as it affects the quality of life, safety, security, health care, and education available to tourists. Destination attractiveness is influenced by various factors, such as wealth, economic growth, education, health, personal well-being, and quality of life. Prosperity includes a variety of factors such as wealth, economic growth, education, health, personal well-being, and quality of life (OBG, 2019). Prosperity affects people's well-being and ability to build a better future (Diener et al., 2010; Diener & Seligman, 2004). Tourists seek out healthy, safe, secure, enjoyable, and peaceful destinations, particularly in the aftermath of the COVID-19 pandemic. Therefore, the happiness levels and overall quality of life in a destination country are important determinants of tourism demand. A higher level of happiness and quality of life is likely to attract more visitors and increase tourist spending. The tangible and intangible factors affecting tourism destination choices include transportation facilities, friendliness of people, quality and variety of food, accommodation facilities, personal safety, price, culture and historical environmental safety, and quality. (Guo & Sun, 2016; Hsu et al., 2009; Li et al., 2017; Unguren et al., 2021). Gholipour et al. (2022) found that tourists spending on traveling higher at happier destinations. Huang et al. (2021) and Lee et al. (2018) concluded that while travel experiences can increase tourists' happiness, destination countries' happiness levels will also attract visitors, enhancing understanding of the demand-generating influence of a destination country's happiness level.

Paniagua et al. (2022) suggested that tourists link happiness with the destination's quality of life and the significance placed on the quality of life of the destination has been growing. According to Hsu et al. (2009) there are tangible and intangible factors affecting tourism destination choices including, transportation facilities, friendliness of people quality and variety of food, accommodation facilities, personal safety, price, culture and historical Environmental safety and quality .as they think the quality of life in the destination impact the decision to choose the destination (Guo & Sun, 2016). Individuals plan to travel by considering the factors that push them away from their current environment and the pull factors that will be acquired through mobility, such as low living costs, climate, the opportunity for prosperity, and a higher quality of life (Unguren et al., 2021). Khalid et al. (2021a) stated that countries with stronger health security capabilities attract a higher number of tourist inflows. In addition, Kazmi et al. (2020) examined the effect of destination service quality on international tourists' intention to return for pilgrimage to Pakistan's sacred sites. The empirical findings indicated that the impact of destination service quality on tourist satisfaction and revisit intention was significant.

In contrast, some countries have been unable to establish themselves as tourist destinations because of the low levels of security, health care, and education. Social welfare and safety are also important indicators of regional social stability and can reduce the number of tourists attracted to a particular destination. According to some studies, factors such economic development, a peaceful society, cultural affluence, transportation service, a pleasant landscape, welfare, and public safety are all significant factors when determining liveability in destinations (Balsas, 2004; Kashef, 2016). Liveability is a significant tourism competitiveness factor and one of the major driving forces of tourism activities that could impact tourism demand. One of the socio-demographic variables that tourism researchers consider is the education level in destination countries. The most important feature of education is that it contributes significantly to human capital. Additionally, human capital is one of the non-economic variables in the target country and is one important factor that has a positive effect on tourism demand (Seetanah et al., 2010; Stauvermann & Kumar, 2017).

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_5: The prosperity of the destination has a positive and significant impact on tourism demand flow in Saudi Arabia.

Relative temperature

Another factor that influences tourism demand is weather or climate. The Mintel International Group (1991) reported that 73 percent of UK respondents cited “good weather" as the main reason why people go abroad. Gössling et al. (2006) found that 53 percent of respondents considered climate a key factor in their choice of destination. Based on a review of destination image studies conducted by Hu and Ritchie (1993), “natural beauty and climate” were universally significant factors in determining destination attractiveness. Many research studies have proven that it is one of the most critical factors influencing tourists' choice of destination.

To measure the impact of climate in tourism demand, Taylor and Ortiz (2009) used the variables of temperature and sunny hours; Kulendran and Dwyer (2012) used maximum temperature, relative humidity, and sunshine hours; Ridderstaat et al. (2014) used rainfall, temperature, wind speed, and cloud coverage; and Goh (2012) used the tourism climate index (TCI). Lorde et al. (2016) used climate distance, which measures the gap between climate conditions in origin and destination countries, and Zhang and Kulendran (2017) used temperature, number of tropical cyclones, rainfall, humidity, number of thunderstorms, and seasonal variation. Li et al. (2018) used a relative climate index, which measures the climatic comfort of a destination relative to that of the tourists’ country of origin. A recent study by Susanto et al. (2020) used monthly average temperature, total precipitation, and average relative humidity of the destination as their variables. This study takes the temperature of tourists’ origin countries into consideration.

Benson (1996), and Giles and Perry (1998) highlighted that domestic tourism increased in the UK during and after a warm summer. Climate encourages international and national tourism flows as visitors look to go to a place that has weather suited to their holiday activity choices (Becken, 2010). Wilton and Wirjanto (1998) found that a one-degree celsius warmer summer increased domestic tourism expenditure by four percent. Lorde et al. (2016) provided evidence that climate distance (the difference between climate conditions in origin countries and destination countries) is a significant demand determinant. Guo and Sun (2016), Li et al. (2017), and Unguren et al. (2021) also argued that climate differences between destination and origin countries attract visitors and impact tourism demand.

Agnew and Palutikof (2006), and Lise and Tol (2002) pointed out that unfavourable temperatures or weather conditions at home, whether during the year of a trip or the preceding year, operate as a motivator for visitors to travel to warmer and drier climates. This implies that when modelling tourism demand, both origin and destination climatic conditions should be addressed, as differences may have influenced demand.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_6: The temperature ratio of the source market to the destination market has a significant negative impact on tourism demand flow in Saudi Arabia.Saudi international students

International students are a well-documented growing market for the tourism industry in the countries where they study. While the market is growing, however, there seems to be a lack of research on the impact on the tourism industry of international students' home countries. The number of international students is growing globally. They usually have a non-resident visa (also known as a student visa) and are studying for a tertiary degree in the destination country (Castillo Arredondo et al., 2018).

Bento (2014) and Weaver (2003) focused on the economic benefits that international students can bring to receiving countries, as these students (inbound tourists) have become a significant long-term investment for the destination. Schänzel and Yeoman (2015) stated that an increase in the number of people who live outside their original home assists in promoting tourism. Recently, the Saudi Arabia government has been encouraging Saudi students who study overseas to promote tourism and improve the image of their country. Saudi students overseas may generate VFR travel when they visit the country during their study period. Moreover, scholarship students may have contributed to raising awareness and improving tourist perceptions and images of Islam and Saudi Arabia, especially important after the September 11 attack. While migration, in general, can have an influence on both VFR and non-VFR tourism, international students specifically have a more pronounced impact on inbound VFR tourism demand. The primary purpose of migration for expatriate workers varies between individuals. When people move to a new country, it can be for reasons such as work, family reunification, education, or seeking a better quality of life. Those who migrate for education purposes, particularly international students, are more likely to have a direct and significant influence on inbound VFR tourism. Their social connections, cultural exchanges, personal recommendations, and emotional bonds allow them to act as powerful catalysts in attracting others to visit the host country.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_7: Students studying overseas have a significant positive impact on VFR tourism demand flow in Saudi Arabia.

Visa restrictions

Most countries require visitors to apply for a visa in advance or when they arrive. International tourist arrivals are reduced as a consequence of the implementation of visa restrictions (Czaika & Neumayer, 2017; Lawson & Roychoudhury, 2016), which also reduces tourism revenue (Khan et al., 2020). It is well known that the visa requirements of a country influence the first impression a tourist has of that country (Chau & Yan, 2021). A number of researchers have noted that visa restrictions have a negative impact on the number of international tourists arriving in the country (Czaika & Neumayer, 2017; Lawson & Roychoudhury, 2016; Neumayer, 2010; Nitsch, 2019; Özdemir & Tosun, 2022; Tang, 2021b).

Neumayer (2010) pointed out that while visa restrictions had a negative impact on international tourist demand flow, they may not have an equal impact on all types of travel. Li et al. (2017) also noted that there is a need to distinguish between the different purpose of travel when it comes to examining the impact of visa restrictions. In the case of Saudi Arabia, eligible international citizens wishing to make a pilgrimage to Mecca have to apply for an Umrah or a Hajj visa (Ekiz et al., 2017). While every physically and financially able Muslim is obliged to undertake the Hajj, Mecca cannot accommodate all those wishing to perform the pilgrimage every year. Consequently, a quota system is in place to ensure equitable distribution of Hajj visas for each country and to regulate the numbers at the holy sites. This quota system was implemented nearly three decades ago under the umbrella of the OIC, with one thousand pilgrims per million inhabitants allowed from each country (Henderson, 2017). However, the Umrah and visits to Madinah can be undertaken at any time of the year without quotas.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis D_8: Visa restrictions have a significantly negative impact on tourism demand flow in Saudi Arabia.

Cultural affinity (common language and religion)

Many applied studies emphasise that countries that share the same language and religion, indicating cultural links and affinity, often have higher levels of tourist exchange than countries that do not share the same language and religion. Sharing a religion, language similarities, and bilateral trade all have a positive impact on international tourist arrivals (Eilat & Einav, 2004; Ghalia et al., 2019; Harb & Bassil, 2020a; Lorde et al., 2016; Morley et al., 2014; Rosselló-Nadal & HE, 2019; Tavares & Leitao, 2017; Vietze, 2012; Wang & Badman, 2016). Fourie et al. (2020) found that differences in language and religion have exacerbated the negative impact of insecurity on tourist arrivals, implying that cultural affinity enables tourists to manage stressful situations better. Ahn and McKercher (2015), Lee et al. (2012), and Ng et al. (2007) suggested that people are attracted to those who share their beliefs and values. An easy way to obtain a travel visa is by sharing a border, or having language similarities, colonial country ties, and bilateral trade. These elements positively influence international tourist arrivals. For instance, Eilat and Einav (2004) found that cultural factors such as shared borders and common languages all play a significant role in the interpretation of tourism demand, particularly in developing countries.

Durbarry (2008) found greater tourist arrival numbers for those sharing a common language compared to arrival numbers of those that did not. Durbarry et al. (2009) found that a common border and language play important roles in tourism demand. When two countries share the same religion or have significant religious similarities, it fosters a sense of cultural affinity and creates a stronger emotional connection between their populations. A common language or effective multilingual services also act as facilitators in reducing communication barriers between countries. This seamless communication enables tourists to interact easily with locals and access information about tourist attractions, thereby enhancing their overall travel experience. In this manner, the presence of shared religion and languages fosters a deeper cultural bond and facilitates mutual understanding, contributing to a more interconnected and thriving tourism industry between the countries involved.

Studies using the gravity model include variables such as common language and common religion in order to capture the qualities of destination and origin countries, as well as the cultural preferences of tourists in choosing a destination (Alawin & Abu-Lila, 2016; Harb & Bassil, 2020a; Vietze, 2012).

In this study, cultural affinity is incorporated as a dummy variable and takes 1 if the bilateral countries share at least one common language, otherwise 0.

After considering the arguments presented above, the following hypotheses were formulated:

Hypothesis $\boldsymbol{D_9}$: Sharing a common language has a positive and significant impact on tourism demand flow in Saudi Arabia.

Hypothesis $\boldsymbol{D_{10}}$: Sharing a common religion has a positive and significant impact on tourism demand flow in Saudi Arabia.

Expatriate workers

Expatriate workers are also important in the context of factors that impact on tourism in Saudi Arabia. According to the GaStat (2021a), the number of expatriate workers account for about a third of Saudi

Arabia's population, approximately 13.49 million in 2021. This makes them an ideal group to study in terms of how immigrants influence tourism demand. As immigrants leave their home country to work and live in a new country, tourism may be stimulated through VFR from their home country. In other words, their friends and relatives who are residents in source countries will have a reason and/or motivation to travel to a destination where there is a larger number of temporary migrants. Migrants who return to their home country for VFR may engage in 'promotion' of their new home, either directly or implicitly, and encourage short-term inbound visits.

Given tourism's significance to the national economy, it is not surprising that the interrelationship between tourism and migration is an area of investigation. While research on migration and its impact on VFR tourism seems limited, the relationship between other forms of tourism and migration are even less visible than VFR (Dwyer et al., 1993; Dwyer et al., 2014). However, the evidence implies that the effect on non-VFR tourism is almost as strong as it is on VFR tourists (Djelti et al., 2021).

The effect of migration on tourism moves in two opposite directions, focused on two different groups in the literature. The first group is migrants inviting their friends and relatives (in-home country) to visit their host country (VFR). Studies in this field focus on the impact of migration on particular countries. Three of these refer to Australia (Dwyer et al., 2014; Seetaram, 2012; Seetaram & Dwyer, 2009); others focus on Canada (Prescott et al., 2005); the US (Tadesse & White, 2012); the UK (Gheasi et al., 2011); New Zealand (Genç, 2013; Law et al., 2013); Portugal (Leitão & Shahbaz, 2012); and Italy (Balli et al., 2016; Balli, Ghassan, et al., 2019; Etzo et al., 2014; Massidda et al., 2015). Almost all these researchers focused *only* on VFR, except for Etzo et al. (2014), and Massidda et al. (2015), who also included non-VFR tourism (such as business and holidays) in their analyses.

The second group is focused on the impact of migration on tourism in the migrant home countries (from the host to the home country) (Balli et al., 2016; Balli, Ghassan, et al., 2019; Provenzano, 2020; Taing, 2019; Takahashi, 2019). In general, there are few studies that investigate the role of migration for non-VFR tourism. According to the trade theory discussed early in this chapter, increased immigration can foster closer economic and social ties between countries. When people migrate, they often maintain strong connections with their home country, leading to enhanced trade and tourism links. These individuals frequently invite their friends and family from their home country to visit them in a temporary destination country. This inflow of visitors boosts tourism demand between the two nations. Immigrants can also serve as a bridge between their host and home countries, facilitating trade and investments between the two.

The number of expatriate workers who live and work in Saudi Arabia was included in this study as a variable to represent migration. A positive relationship between migration and tourism demand was expected.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis$\boldsymbol{D_{11}}$: Expatriate workers have a positive impact on tourism demand flow in Saudi Arabia.

Word-of-mouth effect

Habit formation/persistence and word-of-mouth have played a critical role in influencing tourism demand. The concept of habit formation/persistence means that consumers' current utility is based not just on their current consumption but also on experiences generated by their previous consumption. The word-of-mouth effect means that consumers' current utility is determined by past consumption or information from other customers (Liu, 2020).

According to Garín-Mun (2006), there are two main reasons for including previous consumption as an independent variable: first reason is that there is less uncertainty regarding holidays in a country that tourists are already familiar with compared to travel to a previously unvisited foreign country. Another reason is that awareness of the destination spreads as people talk about their holidays, thus reducing the uncertainty of potential visitors to that country.

For these reasons, if tourists are satisfied with the destination, they will be more likely to return and inform others about their positive experiences with the destination. Thus, the parameter for the lagged dependent variable can be interpreted as a measure of interdependent preferences and habit-forming. Peng et al. (2014) argued that the inclusion of the lagged dependent variable yields efficient estimates consistent with the tourism demand theory.

Incorporating the lagged dependent variable into dynamic plate data models helps increase visibility in developing tourism development policies and strategies. In addition, a lagged dependent variable describes how a destination improves the tourism industry's supply such as hotels, transportation, and skilled staff to meet the growing demand for tourism. It may also capture the influences of various factors affecting tourism demand (Dogru et al., 2017; Habibi, 2017; Rodríguez et al., 2012; Witt & Witt, 1995). In a number of empirical investigations, the estimated coefficients on the lagged dependent variable are positive and highly significant (Afonso-Rodríguez, 2017; Balli et al., 2016; Buigut et al., 2015; Dogru et al., 2017; Fourie & Santana-Gallego, 2013; Garín-Mun, 2006; Garín-Muñoz & Montero-Martín,, 2007; Ghaderi et al. 2017; Habibi, 2017; Habibi et al., 2009; Khadaroo & Seetanah, 2008; Li et al., 2017; Mendieta-Aragón & Garín-Muñoz, 2020; Qiong & Chen, 2018; Rani & Zaman, 2020; Saragi et al., 2021; Song, Witt & Li, 2003; Tang, 2018). However, a few studies found the lagged dependent variable to have a negative effect (Becken & Carmignani, 2016; Lim & McAleer, 2008; Naudé & Saayman, 2005; Toh et al., 2006).

Positive word-of-mouth means tourists have had a satisfying experience in the destination and may decide to visit it again or recommend it to others (Dogru et al., 2017; Peng et al., 2014; Song & Li, 2008). Some argue that returning to a previously visited country is more enjoyable than visiting a country that has never been visited before (Mohammad & Som, 2010; Proenca & Soukiazis, 2005).

Negative word-of-mouth might decrease a consumer's desire to visit a destination (Liu, 2020). Additionally, negative word-of-mouth is more impactful than positive word-of-mouth (Chevalier & Mayzlin, 2006; Mahajan et al., 1984). Since religious tourism is the biggest market in Saudi Arabia and it is a faith-based activity for Muslims, this study aims to examine whether word of mouth has impact on spiritual obligation travel.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis A_1: Word-of-mouth has a positive and significant impact on religious tourism demand flow in Saudi Arabia.

3.4. Gravity models for tourism demand modelling

Modelling tourism demand has relied predominantly on single equation specifications and time series models (Crouch, 1994; Li et al., 2005; Peng et al., 2014; Peng et al., 2015; Song et al., 2019; Witt & Witt, 1995). In this framework, the total number of tourist arrivals to a single destination over a given period is correlated with past behaviour of the same variable and/or depends on macroeconomic time series determinants, including income, price, exchange rate, marketing expenditure, dummy variables, or any other influential measurable factor at the country level.

The use of single equation specifications and time series analysis is justified by the short-term nature of services and the specific requirement of the tourism industry to accurately forecast demand. However, if a tourism demand analysis goes beyond mere forecasting and its objective is to identify specific determinant factors such a particular phenomenon (climate change, diseases, corruption, etc.) or policy (visa policy, tourist tax, etc.) on tourism demand, single equation specifications and time series analysis do not provide a substantial evaluation of regional/cross-country phenomena.

Although the gravity equation has been used widely in other research areas, it was neglected by tourism demand researchers until the 2000s, when the gravity model re-emerged within academic tourism literature. An initial empirical study of gravity equation parameters was conducted with simple linear regressions (other linear regressions), which simplified estimation issues due to the fact that single countries and one simple time period were considered (Crampon & Tan, 1973; Quandt & Young, 1969; Smith & Brown, 1981). However, given that the research examined tourism flows over different periods of time, panel data techniques are necessary in order to examine the determinants of tourism flows from and to different countries and regions during different periods of time. In addition to capturing relevant relationships over time, this dynamic framework avoids the potential risk of choosing an unrepresentative year. In addition, panels can be used to control for unobservable individual characteristics among partners.

A large number of studies have used the pooled ordinary least squares (POLS) econometric method to estimate the gravity model. In the case of panel data, this is the simplest method for estimating linear regression. In POLS, observations are stacked for each individual over time, so differences across individuals are not taken into account. Therefore, the method can be biased and inconsistent if fixed effects are not included and heterogeneity relating to time and country is not taken into account (Baldwin & Taglioni, 2006; Yotov et al., 2016).

However, due to their simplicity, POLS estimation techniques are frequently combined with fixed effects and are often used to benchmark other specification methods. Among the fixed effects that are most frequently included in bilateral tourism data are origin, destination, year-fixed or dyads, and most of them are combined with year-fixed effects. This set of fixed effects controls for the time-invariant country-pair characteristics or destination and origin and time-variant common factors. A combination of POLS estimation with dyadic fixed effects for bilateral data, or origin fixed effects for total tourist arrivals, is equivalent to estimating the gravity model through panel fixed effects (Panel-FE).

Often, Panel-RE estimates are presented alongside Panel-FE estimates, and the Hausman test is used to differentiate between them. The Hausman test indicates that Panel-FE is the best specification for estimating the gravity model for tourism demand, which is in line with the theoretical model developed by Anderson and Van Wincoop (2003). However, the Panel-FE model has the disadvantage of not being able to estimate time-invariant characteristics of origin/destination or country pairs. To estimate the gravity model in a panel data context, it is necessary to examine whether the variables are stationary. To avoid spurious regressions, preliminary unit root tests are required. However, most revised studies do not consider this diagnostic test since they assume the stationarity of dependent and independent variables in order to estimate gravity models. However, this is not always the case since variables such as tourism flows and GDP are likely to be I(1). Therefore, the long-run relationship between these variables can be addressed using alternative methods of estimation of panel cointegration, such as the fully modified ordinary least squares (FMOLS) approach estimator and the panel dynamic ordinary least squares (DOLS) method proposed by Pedroni (1999, 2001), and Kao and Chiang (2000) respectively.

The FMOLS and DOLS are both dynamic panel data models capable of generating efficient estimates for panels with small samples. Panel FMOLS models employ a semi-parametric correction to eliminate potential issues of endogeneity and serial correlation, resulting in asymptotically unbiased and efficient coefficient estimates. In the panel DOLS model, leads and lags of differences between explanatory variables are implemented to correct for possible endogeneity and serial correlations. Although the DOLS and FMOLS methods are highly efficient for estimating dynamic panel data models, they have rarely been applied to estimating tourism demand models. The FMOLS model was employed to estimate tourism demand models in the study by Seetanah et al. (2010). The panel DOLS and FMOLS models are only applicable when all study variables exhibit stationary processes at the same level (Dogru et al., 2021).

Studies can show that some of the variables are stationary at the level I(0), while others show stationary at their first difference I(1). In this case, the panel ARDL method developed by Pesaran et al. (1999) can be used to estimate tourism demand models. Panel ARDL models are also dynamic panel data models. Cointegration tests, such as those performed by Kao (1999) and Pedroni (2004), can determine whether a cointegration relationship exists between study variables. Therefore, the estimated model is asymptotically unbiased, efficient, and consistent as a result of its negative coefficient. Khoshnevis Yazdi and Khanalizadeh (2017) utilised ARDL methods to estimate factors affecting tourist arrivals in the instance of a dynamic panel data model.

The generalised method of moments (GMM) has been used to estimate gravity models in dynamic panel data frameworks. This method addresses econometric problems such as endogeneity, measurement error, and weak instruments, and controls for repeats and loyalty in tourism flows. Both GMM and ARDL apply when the variables are either stationary at level 1(0) or stationary at first difference 1(1). When time series (T) is larger than cross-sectional (N), the ARDL approach is appropriate, whereas when T is smaller than N, the GMM estimator is appropriate.

A more recent approach has been to use the Poisson pseudo-maximum likelihood (PPML) estimator proposed by Silva and Tenreyro (2006, 2010). This deals with biases when estimating gravity equations by POLS in particular, the presence of heteroscedastic residuals and zeros in the dependent variable (although zero tourism flows are less prevalent in tourism data than in trade data).

The UNWTO, which is the principal source for tourism data collection, reports zero tourism flows and it is difficult to distinguish between those that are reported and those that are not. Khalid et al. (2021a), Okafor, Tan, et al. (2021) and Saayman et al. (2016) handle this issue by assuming that the UNWTO does not record tourism flows below a specific threshold, and thus consider the data to be zero or close to zero for small tourism flows.

However, this strategy cannot generate efficient estimates as in some cases aggregations in other countries are not negligible, and the specific threshold for not reporting tourism flows does not apply to every destination. PPML is recommended as a procedure for estimating gravity equations, however it is only used in a limited number of the papers reviewed (Khalid et al., 2021a; Khalid et al., 2022; Okafor, Tan, et al., 2021). Furthermore, alternative methodologies such as quantile regressions (QR) have been used to estimate gravity models (Cheung & Saha, 2015; Chow & Tsui, 2019; Ghani, 2016; Marrocu et al., 2015; Santeramo & Morelli, 2016).

Geographic context and the research objectives are interesting aspects to take into consideration when reviewing the research. In terms of geographical context, there are two main groups. The first group examines the determinants of tourism for a group of countries, and the second group examines a single country. Papers that examine a group of countries are mainly based on information from databases that include bilateral tourism for a large number of countries globally. Additionally, developed countries like the OECD and European countries attract more attention in tourism economics literature. In developed countries, data quality or availability is often higher than in developing countries, which may explain this attention. Several countries have been used as case studies, including China and the US. American scholars were the first to use gravity models, using US data (Long, 1970; Quandt & Baumol, 1966; Quandt & Young, 1969). Chinese scholars have published very recent research on tourism demand that is based on Chinese data (see, for example, Liou et al., 2020; Xu & Dong, 2020). A number of important tourist destinations, including Italy, Spain, and Turkey, have also been chosen as case studies for the application of gravity models to tourism demand.

On the one hand, most research is focused on identifying general factors influencing tourism demand, without focusing on specific factors. The majority of this occurs when the geographical context consists of a single country. In other words, many scholars are interested in country-specific tourist case-study determinants. However, many papers have focused on a particular research topic, highlighting topics related to transport, connectivity, migration, and cultural variables such as religion, language, and cultural values as well as trade and visa policies. Several papers have been published recently, motivated by the international context, that are focused primarily on security threats, mainly terrorism and security expenditure (Fourie et al., 2020; Khalid et al. , 2020; Okafor & Khalid, 2021; Santana-Gallego & Fourie, 2020).

A summary of the determining factors for tourism demand examined in the reviewed major studies is presented in Appendix A. Due to the inability to present all variables in the tourism demand studies that used the gravity model, this study followed Rosselló Nadal and Santana Gallego (2022) in terms of the aggregation of the variables in relevant groups.

The distance variable can be grouped with the geographical distance and travel distance variables, since these two variables are likely to share the same concept. The simplest version of the gravity model illustrates that distance, whether in terms of geographical or travel distance, or travel cost as well as economic size or population are the most frequent explanatory variables included in this model. Most papers include distance, while travel costs are less frequently included. It is important to note here that the economic size of the origin country and destination country, measured in terms of GDP and population is more frequently considered than the population. Moreover, prices are commonly considered in gravity estimations. As a result, price and exchange rate variables are utilised (price is considered more inclusive than exchange rate). The variables are generally expressed in terms of the prices/currencies of the destination compared to the prices/currencies of the origin. However, there are fewer economic variables that measure the intensity of economic relations. For example, few studies using the gravity model for tourism demand include trade variables, trade agreements, sharing a common currency, visa agreements or other economic-related variables. Furthermore, common borders and other geographical variables are often included as part of this type of specification, as indicators of accessibility to the tourist destination. While time is another geographical variable, it is less commonly included.

Infrastructure is also often referred to as an accessibility variable. This includes transport infrastructure and air connectivity. Variables related to the environment and climate are rarely included in the literature. In gravity models, cultural variables, such as common languages or colonial ties, are frequently employed. Other variables have become increasingly more important in the literature, such as World Heritage Sites, cultural affinity, migration, religion and other sociological, cultural and economic variables (e. g., internet users, mobile phone users, life expectancy, education level etc.).

Variables related to politics and institutional quality are also considered. It is becoming more common in gravity models for tourism demand to include security threats such as crime, armed conflicts, and terrorist attacks, or special events that may affect tourism, such as the Olympics, SARS, or other crises.

3.5. Tourism demand forecasting

Tourism forecasting approaches can be divided into two groups based on the available data: quantitative forecasting and qualitative forecasting.

Quantitative forecasting uses statistical and econometric techniques (Isik et al., 2018; Işık et al., 2020). Makridakis and Wheelwright (1989) stated that quantitative forecasting is used based on the following three aspects: adequate past data, data that can be quantified numerically, and certain aspects of past trends can be expected to be repeated in the future. Quantitative techniques attempt to predict the future by analysing past patterns and the link between variables that influence demand (Calantone et al., 1987).

Quantitative approaches dominate the tourism literature and are particularly beneficial in short-term forecasts since the relationships between the variables will likely remain constant. As relationships are longer, they tend to become less stable and quantitative prediction accuracy declines. The primary weakness of quantitative forecasting has been its reliance on aggregated data (Uysal & Crompton, 1985). The unavailability of data also restricts its application in particular tourist projects.

Qualitative forecasting methodologies are appropriate when very little quantitative data is available but adequate qualitative knowledge exists. Significantly, Archer (1987) identified three major situations in which qualitative forecasting is recommendable: data are inadequate or are known to be inaccurate; an appropriate numerical model cannot be built; and there is insufficient time to initiate and run a quantitative study. Qualitative approaches include those that are more subjective (Uysal & Crompton, 1985). Qualitative forecasting, which does not require any mathematical formulas, is based on specialists' intuitive reasoning, judgement, and accumulated experience.

Quantitative approaches include time series regression, neural network models, and other econometric models (Kaplan & Aktas, 2016; Kulendran & Witt, 2003b; Song & Turner, 2006; Uysal & Crompton, 1985). But these methods are ineffective when the future is uncertain or no comparable experience exists. Quantitative methods cannot predict any lack of historical data (Schnaars, 1987).

Qualitative methods can be used to forecast the future in these instances because they do not require previous data (Frechtling, 2012). As noted above, these qualitative strategies are appropriate when past data is insufficient or inappropriate for forecasting the future (Uysal & Crompton, 1985). Liu et al. (2021) pointed out that unstable explanatory variable forecasts may reduce the forecasting accuracy of econometric models. Indeed, this is one of the forecasting difficulties associated with the COVID-19 crisis. The Delphi method, traditional survey methods, judgement-aided models (JAM), and scenario analysis are all types of qualitative forecasting techniques (Calantone et al., 1987; Frechtling, 2012; Uysal & Crompton, 1985).

Due to the perishable nature of the tourist product, including hotel rooms, airline seats, and cruise-ship lines, accurate forecasts of demand are critical for planning and management (Song et al., 2009). Public and private investments in the tourism industry are also heavily dependent on accurate forecasts of the industry's future.

Accurate forecasts of tourism demand provide critical information for policymakers, government and strategic planners at destinations. Tourism's dynamic nature, as well as its importance to worldwide economies, needs further research to increase the precision of its practical consequences. Policymakers require precise forecasts in order to allocate money for tourism infrastructure development, such as hotel facilities and public transportation. It is impractical to keep unsold airline seats and hotel rooms due to the perishable nature of tourism goods. As a result, precise forecasts of business demand are critical for professionals to make effective business decisions, such as hiring and pricing strategies.

Tourism marketers use demand predictions to develop appropriate marketing goals and explore potential markets (Frechtling, 2012). Furthermore, tour operators, accommodation providers, event organisers, and retailers, along with all other members of the tourist value chain, need reliable forecasts to make short-term choices and to examine long-term trends and define priorities (Law et al., 2019; Sun et al., 2019; Wan & Song, 2018). Accurate forecasts would enable customers to prepare in advance and allocate resources more effectively, and businesses might be able to adjust their strategies to improve their efficiency.

The significance of the forecast is its capacity to minimise the loss caused by demand-supply disparities. Destinations must obtain credible estimates of future demand for accommodation, transportation, service employees, and other relevant travel services in order to offer excellent services for tourists (Wang & Lim, 2005). Louw and Saayman (2013) suggested that a lack of comprehension of future tourist arrivals could lead to missed opportunities or an overestimation of the demand for tourism. Excessive investment, for instance, can result in an over-evaluation of tourism demand. Therefore, prediction is a vital aspect of the overall tourist sector strategic planning process. There has been a rapid expansion of international tourism as a result of social, economic, political, and technological developments. As more tourist destination countries/regions compete for scarce resources, this trend can lead to a mix of costs and benefits (Lim, 2006).

The next section discusses the overall trends and evolution of tourism demand forecasting methods, including time series, econometric, AI-based, and judgmental methods.

3.5.1. Time series models

Time series models forecast tourism demand based on historical trends. These models aim to classify time series data patterns, slopes, and cycles (i.e., using sequences of measurements made during successive periods). Time series forecasting models are based on successive values that reflect consecutive measurements taken at regularly spaced intervals (such as monthly, quarterly, or annual measurements). If a pattern is formed, time series models predict the future values for the time series to come. Time series models are further classified as either simple or advanced time series techniques (Song et al., 2019).

In general, the basic types of time series models are naive (no change models), moving average (MA) autoregression (AR), and exponential smoothing (ES). The time series models have been widely used in tourism demand forecasting studies due to their ease of implementation and the ability to capture historical patterns. The naive and exponential smoothing models are non-statistical time series models. Song et al. (2019) found that 55 studies of 211 reviewed used basic time series models, the naive-1 and naive-2 models among them. The naïve-1 or no change model assumes that a forecast of a series at a certain point in time equals the actual value at the previous point in time. The naive-1 model has been the simplest approach and has often provided more accurate short-term forecasts than other more sophisticated models (Li et al., 2006; Witt et al., 1994; Witt & Martin, 1987). However, when dealing with unexpected systemic change and longer-term forecasting, the naive-1 model's performance declines (Chan et al., 1999; Chang et al., 2009; Witt et al., 1994).

The naive-2 model is also another common simple model utilised if there is a consistent pattern in the data. The naive-2 forecast is the current value multiplied by the growth rate between current and prior values. The naive-1 and naive-2 approaches are the most widely used and broadly accepted in the tourism forecasting literature. As noted above, despite their simplicity, these models produce reasonably accurate predictions, especially for short forecasting horizons (Assaf et al., 2019; Claveria & Torra, 2014; Song et al., 2011).

Numerous researchers have employed exponential smoothing in forecasting. A smoothing model is based on the basic idea of constructing forecasts of future values by weighting observations of the past and giving greater weight to observations of the recent past than to observations from the distant past (Yonar et al., 2020). Ostertagova and Ostertag (2012) highlighted that the exponential smoothing model is a widely used time series analysis technique. Jere et al. (2019) used Holt-Winter's exponential smoothing model to forecast yearly international visitor arrivals in Zambia and compared it to the autoregressive integrated moving average (ARIMA) model. When there is no trend or seasonal pattern, the simple exponential smoothing (SES) model is used to forecast a time series. According to Chen et al. (2008), SES is perfectly applied for a time series with no clear trend or seasonal pattern.

Advanced time series models vary from basic time series models in that they adopt additional time-series features such as seasonality and trends. Among the various types of advanced exponential smoothing models, numerous kinds of trend analyses and Box-Jenkins methods such as autoregressive integrated moving average (ARIMA) methods (Box et al., 2015).

Time series forecasting using exponential smoothing is a popular technique that predicts future values based on weighted averages of past observations. As an extension of the basic exponential smoothing concept, advanced exponential smoothing models incorporate additional factors, such as seasonality and trends, which increase the accuracy of forecasts. When the data shows a clear upward or downward trend over time, trend analysis is one type of advanced exponential smoothing model that is applied. In trend analysis models, a trend component is integrated into the forecasting equation, allowing it to take into account changes in the underlying pattern of the data.

Additionally, the Box-Jenkins method involves several steps and constitutes an advanced exponential smoothing model in terms of time series forecasting. In addition to identifying and removing trends, seasonality, and other patterns, the Box-Jenkins method also identifies and selects appropriate forecasting models based on the data.

ARIMA methods, are commonly used or have been attracting increasing attention (Gounopoulos et al., 2012; Lim & McAleer, 2002). It is a quantitative approach widely used in the forecasting of so-called ARIMA. It is a model in time series that describes a variable in relation to its history and a random term of disturbance. The historical trends and patterns (such as seasonality) of the time series concerned are investigated. In this context, the future of this series is predicted on the basis of trends and patterns found in the model. Since time series modelling needs only historical variable measurements, data collection and model estimation are less expensive. It has had great success in academic research as one of the most common linear models of time series forecasting (Coshall & Charlesworth, 2011; Goh & Law, 2002; Kulendran & Shan, 2002; Law & Au, 1999; Lim & McAleer, 2002).

A range of ARIMA models have commonly been used in the time series analyses of tourism demand. Since these ARIMA models take into consideration both current and lagged observations (AR components), random shocks (MA components), and degrees of integration (I components), they seem to be very flexible in modelling tourism demand. In Song et al.'s (2019) review of the literature, ARIMA-type models were used 103 times in a collection of key studies, accounting for 74 of the 211 works reviewed. ARIMA-type models account for more than 60 percent of the papers that use time series methods (118 papers). Among the 74 studies that used ARIMA-type models (noted above), 56 noted that these significantly outperformed other techniques in determining at least one destination and forecast horizon (Du Preez & Witt, 2003; Kulendran & Witt, 2001). The seasonal autoregressive integrated moving average (SARIMA) (often seasonality adjustments [S components]) is also one of the forecasting techniques used in the tourism market and a number of studies (Fahrudin, 2018); Rufino, 2016); Thushara et al., 2017).

Leading indicators have been widely utilised in business for forecasting turning points as well as uniform calendar time units in the business world. While the leading indicator approach is sometimes referred to as measurement without theory, economic theory does provide guidelines for selecting variables. Choi et al. (1999) previously examined the cyclical patterns of business activity in the hotel industry and indicated that further research was required for the development of a leading indicator. A number of explanatory variables were initially considered as potential leading indicators of inbound tourism demand, including tourist-origin country income and relative price adjusted with the exchange rate. Kulendran and Witt (2003b), and Turner et al. (1997) conducted research on the effectiveness of using leading indicators, including the income of the tourist's country of origin, exchange rates, and relative prices, to predict quarterly tourism demand. Rosselló (2001) found that the leading indicator approach outperformed time series models such as ARIMA and naive in predicting turning points.

The autoregressive integrated moving average with explanatory variable (ARIMAX) models, on the other hand, place a strong emphasis on predicting the dynamics of tourism demand. Li et al. (2018) investigated the impact of relative climate variability on tourism demand using an autoregressive-exogenous (ARX) model. It is worth mentioning that the ARX model has the same functional structure as a reduced autoregressive distributed lag model (ARDL) and is also recognised as a partial adjustment model (Hendry, 1995). In terms of forecasting hotel occupancy, the time series model outperforms the ARMA model (Pan & Yang, 2017). Tsui et al. (2014) found that the ARIMAX model produces better long-run forecasts than that of the SARIMA model when forecasting airport passenger numbers in Hong Kong. ARIMAX-type models, like the ARDL and ECM, perform well when combined with static varying parameters (VP) and mixed-data sampling (MIDAS) features for modelling and forecasting tourism demand (Bangwayo-Skeete & Skeete, 2015; Pan & Yang, 2017).

The basic structural model (BSM) is another extension of time series models with exogenous variables. The structural time series model (STSM) can examine the effect of exogenous variables in particular, with a focus on patterns and seasonal and cycle components by including explanatory variables in the BSM. Such applications of the STSM in tourism demand modelling and forecasting can be found in Greenidge (2001), Guizzardi and Stacchini (2015), and Ognjanov et al. (2018). Another stream of thought extends further than the static single equation model to account for the interdependence of multiple demand equations or time series. Rather than modelling demand using a single equation, this line of research estimates and forecasts tourism demand employing multiple equations. Greenidge (2001) proved the efficacy of BSM in forecasting international tourists to Barbados, indicating that it provided useful insights into tourist behaviour. However, the BSM does not take into account the determinants of external factors on the variable of interest. To overcome this constraint, exogenous variables can be incorporated into the BSM to produce an STS with explanatory variables, referred to as the casual structural model (CSM).

3.5.2. Econometric models

The use of economic forecasting models to explore causal relationships between economic factors and tourism demand has been of increasing interest over the past few decades. Economic models have the advantage of being able to capture the causal relationship between tourism demand and the factors influencing it, providing the ability to explain, and forecast changes in tourism demand. An econometric model is not only useful in predicting future tourism demand; it can also be used to explain the reasons for changes to tourism demand in order to provide policy recommendations and evaluations (Goh & Law, 2011; Li et al., 2005; Song & Li, 2008). Tourism demand is influenced by a variety of factors, such as weather conditions (Day et al., 2013; Goh et al., 2008; Grigorieva, 2019), holidays (Y.-Y. Liu et al., 2018), seasonal patterns (Chen, 2015), economic factors (Goh & Law, 2002; Görmüş & Göçer, 2010), among others (Martins et al., 2017; Poprawe, 2015; Viljoen et al., 2019).

In the past five decades, the constant development in econometric forecasting has aimed to identify the causes and effects of economic factors and the demand for tourism in different empirical contexts. While time series models indicate the patterns in a historical data series may shape the future, the econometric models alternatively concentrate on determining the causal structure or how the different reasons influence future demand. The econometric forecast models begin with the setting of potential causality, which is supported by demand theory, and then sort out the defective from the efficient variables. In performing this approach, econometric forecasting models often play a distinguishing part in the performance of tourism demand forecasting.

The most common basic econometric forecasting model is single static regression (SR), which adopts POLS estimation (Crouch, 1994; Uysal & El Roubi, 1999; Witt & Witt, 1995). The key purpose of such simple models is to estimate the impact of several variables causing current values (Song et al., 2019).

It is important to note that the constant elasticity structure of these models has numerous problems, including spurious regression and absurd results when the independent variables extend beyond their original ranges (Kanafani, 1983; Li et al., 2004; Song & Li, 2008). Several of the initial studies in tourism analysis fall within this category (Witt & Martin, 1987). In later years, SR has been used as a benchmark for the forecasting of tourism demand (Athanasopoulos et al., 2011). The econometric approach to modelling and forecasting tourism demand has been improved in order to avoid the spurious regression that is often associated with SR analysis based on OLS, as well as to take into account the intertemporal relationship between tourism demand and various independent variables. Dynamic models have appeared in the literature of tourism demand since the mid-1990s, including the distributed lag (DL) model, its advanced counterpart, the ARDL, and the ECM.

In particular, the DL models take into consideration not only current values but also previous values of the factors that decide the current demand for tourism. Nevertheless, because of competition from its more general, advanced counterpart, the ARDL the application of DL models in tourist demand forecasts is restricted. The DL models are usually used as one of the benchmarks in prediction and comparison assessments (Guizzardi & Stacchini, 2015; Wan & Song, 2018). ARDLs often integrate the impact of lagging demand variables in addition to the assessment of the effect of lagged influencing factors.

Furthermore, based on the ARDL basis, the ECM takes into account both the long-term relationship between the demand for tourism and its influencing factors, and the short-term error correction mechanism in determining the demand for tourism. Both the ARDL and the ECM (also called the cointegration model) play critical roles in the study of tourism demand (Wu et al., 2022). In Song et al. (2019), of the 211 key papers reviewed, they found 111 papers used an econometric approach. Among these studies, 26 used the ARDL and 24 used the ECM, meaning that these models were used in almost half of the studies that had chosen an econometric method (Kulendran & King, 1997; Smeral, 2010; Song, Witt, & Li, 2003). Overall, the ARDL and ECM perform excellently when it comes to modelling or forecasting tourism demand. Sixteen of the 26 papers that examined the ARDL found it to be the "best performing" model. Of the 24 papers that tested the ECM, 17 found it to be the "best performing" model among the different alternative models used in those studies. Because of its flexibility, the ARDL can be combined with other features that reflect parameter assumptions or data utilisation. For example, the time-varying parameter (TVP) has been found to work well with both the ARDL and the ECM for capturing gradual structural changes (Li et al., 2006; Song, Witt, & Jensen, 2003). MIDAS is combined with a simplified version of ARDL to estimate tourist arrivals in the Caribbean, using mixed-frequency data (Bangwayo-Skeete & Skeete, 2015). The authors of that study used the term 'AR-MIDAS', indicating that the functional form of the model used is a partial adjustment model or a reduced ARDL. Whereas the ARDL and ECM extend the static single equation model by incorporating time dynamics, the already dynamic time series models can be offered equal extensions by including explanatory variables. One of these models is the ARIMAX model, where X represents the explanatory variables. The ARDL and the ECM highlight the measurement of the connection between the determinants and the demand for tourism.

One extension is the almost ideal demand system (AIDS). AIDS has been strongly based on the economic theory since its introduction in the 1980s (Deaton & Muellbauer, 1980). This method has showed the ability to capture demand for specific products and services, as measured by market share within an economic system. Concerning modelling and forecasting tourism demand, various forms of AIDS have been used to estimate the market shares of US tourists to Europe (O'Hagan & Harrison, 1984). Other related studies estimated Australian inbound demand through several international markets (Divisekera, 2003). Another study estimated consumption expenses in 13 European countries for different tourist products and services (Lanza et al., 2003). While a classical model, AIDS is determined in a static system, but the model could easily be converted into a dynamic system. Li et al. (2004) and Li et al. (2006), for instance, integrated ECM features into AIDS and found that dynamic AIDS models are highly effective when it comes to forecasting UK tourist demand for different European destinations. TVP technology can also be combined with ECM-AIDS and AIDS models to boost forecasts of demand and tourism expenditure (Li et al., 2006).

Another kind of extension of the single static equation model is the VAR model and the vector error correction model (VECM). These expansion models can capture the interdependence of multiple time series. All of the explanatory variables in a VAR system are considered endogenous, with the assumption that they all influence each other intertemporal. The VAR model has been used in tourism demand forecasting since the late 1990s (Kim & Song, 1998), among these studies are Assaf et al. (2019), Blunk et al. (2006), Song and Witt (2006), and Wong et al. (2007). Only Blunk et al. (2006), and Song and Witt (2006) found that the classical VAR model is promising in terms of predictive efficiency. Other modern econometric techniques often outperform the classical VAR in many instances (Song & Li, 2008). Wong et al. (2007) introduced the Bayesian VAR (BVAR) model, in an effort to improve the efficiency of the classical VAR model, by introducing informative constraints (Bayesian priors) in model estimation. They noted that the BVAR outperformed its non-Bayesian equivalent in forecasting.

Pesaran et al. (2004) extended the classical VAR model into a global VAR (GVAR) system. Assaf et al. (2019) improved on this method by introducing Bayesian estimation techniques (BGVAR) for modelling and forecasting demand for international travel within Southeast Asia. Doan et al. (1984), and Litterman (1986) made early efforts to apply the model. More recently, the BVAR method has been applied more systematically for policy research and forecasting macroeconomic variables (Caraiani, 2010; Kadiyala & Karlsson, 1997; Koop, 2013). There has also been an increase in the use of BVAR models in scenarios with big datasets (Berg & Henzel, 2015).

However, while various successful applications of BVAR models to macroeconomic forecasting have been documented in the literature, they are almost unexplored in the field of tourism demand modelling and forecasting. BVAR models and their unrestricted VAR equivalents were both evaluated by Wong et al. (2006), who have been the only ones to do so. Unrestricted BVAR models were shown to be less accurate than BVAR models for predicting Hong Kong's tourism demand. GVAR and BVAR models, as shown in the preceding literature analysis, are superior to typical VAR models when it comes to simulating large systems. They each avoid the over parameterisation problem by approaching it from various angles. If the number of variables included in the first stage of the GVAR specification is big, or if relatively lengthy lag structures are included when quarterly or monthly data are used, the number of parameters to be estimated via a two-stage modelling technique may still be large. For better model estimate and forecast accuracy, it is necessary to reduce the parameters even lower. The Bayesian method to GVAR modelling is a potential solution, but this has yet to be used in any tourism forecasting study to my knowledge.

The TVP method takes into account the potential changes of a parameter over time and therefore overcomes the external shock to the structural instability problem. Song and Witt (2000) suggested that TVP can be simulated by various kinds of external shocks to the tourism demand environment, including policy and system changes, economic reforms and political instability. In addition, the TVP model successfully captures incremental and diffuse external forces, including changes in consumer preferences and other psychological and social patterns. Song et al. (2009) stated that the TVP model provided the most accurate short-term forecast, based on an analysis of tourist arrivals in the UK and the US. This is consistent with previous studies (Song et al., 2000; Song, Wong, et al., 2003). Witt et al. (2003) examined the Danish tourism market and stated that the TVP model performed consistently well for one year ahead forecasting.

Finally, researchers have also combined ARDL and ECM with TVP techniques to improve forecasting accuracy (Fildes et al., 2011; Song et al., 2011). The flexibility of the ARDL allows its use with other features that represent parameter assumptions or data utilisation. TVP has been demonstrated to be effective when combined with both the ARDL and the ECM when capturing gradual structural changes (Li et al., 2006; Song, Witt, & Jensen, 2003). To forecast tourist arrivals with mixed-frequency data, Bangwayo-Skeete and Skeete (2015) combined MIDAS with ARDLs (partial adjustment models). Considering that the ECM is effective in overcoming spurious regression problems and capturing short-term dynamics, and that the TVP model is capable of capturing structural instability, Li et al. (2006) combined these two models and found that this newly generated model outperformed the individual models.

Since the econometric method can evaluate causal relationships between the dependent and explanatory variables for tourism demand, it has a key advantage over the time series models.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis F_1: Econometric models provide better forecasting than time series models.

3.5.3. Combination forecasting method.

Given the ambiguity of previous models' performance, an emerging trend of using combined and hybrid models for tourism demand forecasting became evident. In their pioneering analysis of forecast combinations in the tourism sector, Fritz et al. (1984) stressed that the combination of several competing forecasts can minimise errors and achieve improvement in overall forecast performance accuracy. Despite the fact that the first combined forecast was made quite early (Fritz et al., 1984), the majority of combined and hybrid forecast research has been carried out since the late 2000s and increased from 2010 (Wu et al., 2022). Chan et al. (2010) pointed out that a decision-maker may have numerous forecasts, and dismissing any one of them could lead to the loss of essential information. Therefore, Bates and Granger (1969) introduced the use of combination forecasts in the general field of forecasting. In fact, prior to 2008, the use of combination forecasts in tourism was rare, with only four studies found to use this approach (Fritz et al., 1984; Oh & Morzuch, 2005; Wong et al., 2007).

According to Song et al. (2019), 21 of the 24 studies conducted to date using this approach found that combined or hybrid forecast models significantly outperformed other forecasting techniques. They expected that combined and hybrid forecasting models would develop further and play an increasingly important role in the forecasting of tourism demand in the future. The reason for combining forecasts is that greater accuracy can be obtained by combining the data found in individual forecasts into a composite forecast (Bates & Granger, 1969). Bunn (1989) defined this approach as “data-intensive forecasting” because it takes advantage of the availability of multiple information and computational resources to improve forecast accuracy. Another major reason for combining forecasts is to avoid the complexity and risks associated with model selection. Forecasting combination has been widely used in business and economics over the last four decades and, as stated by Shen et al. (2008), most studies have found that combination forecasts outperform single forecasting methods in terms of accuracy.

Even though concept of combining forecasts has received increasing academic attention, it is still considered a new development in tourism forecasting (Wu et al., 2017). Combination forecasts have been used in tourism (Fritz et al., 1984; Oh & Morzuch, 2005; Song et al., 2009; Wong et al., 2007), and the results from these studies have highlighted what could be achieved by using combination forecasts in tourism. Fritz et al. (1984) combined the forecasts from the Box–Jenkins stochastic time series and conventional econometric methods. Three combination techniques were used by Wong et al. (2007). Forecasts were constructed using four forecasting models (ARIMA, ECM, ARDL and VAR) to examine whether multiple forecast models can consistently outperform single forecast models. The results of the study demonstrated that combining forecasts is not consistently superior to the best single model forecasts, but that it always outperforms the least satisfactory forecasts. This finding is consistent with that of Oh and Morzuch (2005). Chen (2011) compared three single model forecasts with six combination model forecasts and concluded that combining the forecasts can improve forecast accuracy.

Few studies have included modern econometric models in their comparisons. Notable exceptions are studies conducted by Shen et al. (2008), Song et al. (2009), and Wong et al. (2007). Since econometric models are based on various assumptions about the form that the relationship between variables follows (e.g., endogeneity in the VAR model and homogeneity in many others), or use different estimation methods (e.g., the TVP model employs the Kalman filter algorithm), their model properties vary from one another and from time series models (Shen et al., 2011). Bates and Granger (1969), and Wu and Blake (2022) stated that combining models with independent variables is most likely to increase forecast accuracy.

Individual model forecasts can be combined in a variety of ways, including using average-based techniques, regression-based integrations, and forecast error-based weightings. The average-based methods employ Pythagorean tools (arithmetic, geometric, or harmonic) to combine individual forecasts. This method of combination is easy to utilise, and the weights assigned to individual forecasts are irrelevant to the forecasting methods (Coshall & Charlesworth, 2011; Wong et al., 2007). Individual forecasts are considered to be input variables in regression-based methods and they make linear or non-linear regressions to outfit the actual values (Cang & Yu, 2014; Shen et al., 2008). Forecasting error-based methods are based on the work of Bates and Granger (1969), and they give more weight to best forecasting models that have fewer out-of-sample errors than the worst performing models (Coshall, 2009; Fritz et al., 1984).

The SA method is a simple forecast combination method in which the arithmetic average of individual forecasts is used to calculate composite forecasts. According to Clemen (1989), this method is impartial, robust, and has a good track record in economic and business forecasting, so it is a popular choice for combination forecast studies (Shen et al., 2011). Another forecast combination method is the variance-covariance (VACO) method. This was first introduced by Bates and Granger (1969). The weights are calculated via this procedure by a covariance matrix, which reflects the exactness of the single predictions in the variances, and the covariance interprets the dependence between the single forecasts. Winkler and Makridakis (1983) used a simple combination method and five variants of the VACO method were examined. They stated that some procedures of VACO are more accurate than simple combination techniques and single forecasts, and sometimes more accurate than those where covariance is ignored. Granger and Ramanathan (1984) showed that the optimal weights of a combination of variance and covariance can be calculated by a regression model, and this technique has since attracted considerable attention among scientists.

Empirical findings indicate that, in some cases, the SA approach can generate accurate predictions. Makridakis and Winkler (1983) tested the efficacy of this basic forecasting combination technique in the SA for a number of models. Their analysis showed that the average accuracy improves with increasing combined methods. The benefits and the forecasting efficiency of SA techniques were also explored by Palm and Zellner (1992). They claimed that combining forecasts can reduce error rates and that a straightforward average combination is robust compared with weighted average combinations. Fang and Xu (2003) pointed out that the SA system output was superior to that of single forecasts. Several studies on weighted average combination methods have also been published. These methods measure weights on the basis of each forecasting model's previous performance.

After considering the arguments presented above, the following hypothesis was formulated:

Hypothesis F_2: The combination forecast method provides a better forecast than individual forecasting models.

It is determined whether a forecasting model is accurate by comparing forecasts to actual values. The deviation between an actual value and a forecast is referred to as a forecast error. While not actually an error, the word 'error' refers to the unpredictable nature of observation in this case (Wu et al., 2022).

Forecast accuracy can be measured in a variety of ways. The mean absolute percentage error (MAPE) and the root mean squared error (RMSE) are the most common metrics used to measure the accuracy of models and for comparing the performance of different forecasting methodologies (Ciechulski & Osowski, 2021; Ostertagova & Ostertag, 2012). Since MAPE measures relative performance, it is the best measure of forecast accuracy between different products or items. RMSE is a measure through which predictions are compared to measured true values based on Euclidean distance.

3.5.4. Artificial intelligence (AI) methods

The data-driven and model-free methods used in AI-based models are capable of explaining non-linear data without prior knowledge of the relationships between dependent and independent variables. The artificial neural network (ANN) model, as the most commonly used AI-based technique, has been shown to have good viability and versatility for processing imperfect data or dealing with almost any form of non-linearity. These capabilities explain why ANN models have become valuable tools in forecasting studies (Song et al., 2019).

Although it has been shown that neural network models have superior forecasting performance compared to linear and non-linear models, researchers have often questioned their explanatory value (Law & Au, 1999; Pai & Hong, 2005; Uysal & El Roubi, 1999). Zhang et al. (1998) stated that ANN models are often criticised for lacking a theoretical foundation and for containing a 'black box' of hidden layers between the input and output variables. The input variables used to forecast the outputs are difficult to separate within the network, and the transparency of the optimisation method (for changing weights) is often neglected. The fundamental problem with the 'black box' design of AI-based models is that a small volume of liquid can be mathematically represented, but it would be difficult to reflect an ocean (Robbins, 2016). Over the past few years, ANN studies have garnered attention in a number of fields, such as computer engineering, biology, and economics. ANN models have also been used in other forms of research, including new tourism services' success indicators and analysing the usage of mobile social tourism shopping (Alamsyah & Friscintia, 2019).

Pattie and Snyder (1996) used the neural network approach to forecast demand for tourism with reasonable success. After their research, in the late 1990s, other studies began comparing neural network forecasting performance and conventional prediction techniques. An increasing body of literature began comparing the forecasting performance of ANN models to that of traditional statistical methods, such as regression based and ARIMA models. According to Claveria and Torra (2014) and Lin et al. (2011), ARIMA models outperform ANN models. However, other studies, such as Chen et al. (2012) and Marcellino (2005), provide empirical evidence in favour of ANN models. In a study by Teräsvirta et al. (2005), ANN models were found to be more accurate at long forecast horizons.

Due to the small sample size of the datasets adopted in this study, such methods as the artificial neural network method were not considered. While AI-based models are efficient, they are very dependent on the availability of large volumes of data.

3.5.5. Judgmental methods

It is important to note that statistical methodologies cannot forecast for the effect of unexpected events, such as diseases, disasters, and other crises. To enhance their performance under such conditions, statistical forecasts should be adjusted using judgmental approaches.

To improve the forecasting accuracy of statistical forecasts, experts apply their domain expertise and up-to-date information to gauge the influence of various events and apply the necessary adjustments (Armstrong & Collopy, 1998; Sanders & Ritzman, 2001). This approach combines quantitative models with qualitative judgment obtained through qualitative methods (Song et al., 2013; Zhang et al., 2021). Through the application of judgement, an individual expert or a group of individuals can provide a comprehensive and definitive description of future developments. A number of studies have been conducted on long-term forecasting for tourism demand as well as *ex-ante* forecasting for tourism demand during crises (Lin et al., 2014; Uysal & Crompton, 1984).

Qualitative methods have been criticised for their tendency to introduce human bias. However, since quantitative and qualitative forecasting methods complement each other, the forecasts generated by integrating qualitative and quantitative forecasting approaches are likely to be more accurate than those generated by either of these methods separately (Wu et al., 2022) Judgmental approaches provide a comprehensive explanation of future developments by combining forecasting (quantitative) and the experience of experts or groups of people (qualitative).

Scenario analysis and Delphi techniques are widely used in judgmental forecasting (Uysal & Crompton, 1985; Zhang et al., 2021). Tideswell et al. (2001) combined forecasts of time series with surveys by Delphi for better results. Using Delphi surveys, Lin (2013) and Lin et al. (2014) enhanced the accuracy of forecasts compared to single statistical forecasts by incorporating judgmental adjustments. Lee et al. (2008) confirmed the outstanding accuracy of the integrated forecasting method. Smeral (2010) proposed two scenarios to forecast international travel demand during the economic crisis of 2009–2010, based on the scenario analysis approach. Furthermore, Chauvet and Potter (2013) forecast the growth of US output during the recession based on projections made by Delphi panellists utilising the most recent information available.

Alessi et al. (2014) applied the scenario-based approach to predict macroeconomic variables, the unemployment rate, GDP growth, and inflation, in response to a global financial crisis. During crisis scenarios, these studies found that traditional forecasting methods were less accurate; judgmental forecasts exhibited superior forecast accuracy compared to alternative models. A combination of econometric and judgmental methods has been employed to forecast Hong Kong's tourism recovery prospects post-COVID-19 (Zhang et al., 2021). Baseline forecasts were generated using the ARDL and Delphi adjustments were performed in accordance with various recovery scenarios to reflect the severity of the pandemic. Additionally, these forecasts were used to assess the economic impact of the COVID-19 pandemic on the Hong Kong tourism industry.

3.6. Summary and conclusion

This chapter provides a comprehensive review of recent research pertaining to the modelling and forecasting of tourism demand. It critically examines the key factors that influence tourism demand, beginning with an exploration of the theoretical literature on tourism demand. Notably, two types of theory, namely traditional demand theory and the gravity model, have significant implications for tourism demand models. Empirical research on tourism demand models spanning several decades, from the 1960s onwards, is thoroughly surveyed. The review underscores the crucial elements that shape international tourism flows, including the primary influencing factors, the expected direction and magnitude of these relationships, the frequency of data collection, the specific region or country of interest, the econometric methods employed in modelling and forecasting tourist demand, and the principal findings of empirical studies. Gravity models, unlike traditional demand theory, extend beyond income, prices, or exchange rates as determinants of tourism demand, incorporating a broader range of factors. However, empirical research on the impact of non-economic factors remains inconclusive, with limited emphasis on these elements in the analysis of tourism demand. Moreover**,** expatriate workers, international students and languages are related to trade theory and may reduce trade barriers and encourage tourism flow.

This thesis makes significant contributions to the field by introducing a novel comprehensive demand model that incorporates additional explanatory variables. Notably, it focuses on Saudi Arabia as a destination and examines disaggregated tourism based on the purpose of visits. In this study expatriate workers, international students and languages are related to trade theory and can reduce trade barriers and encourage tourism flow. The study also compares the impact of these factors on tourism demand. It employs time series and econometric models, as well as combined forecasting methods, to forecast tourism demand in Saudi Arabia, with source market pairs, and new explanatory variables. By evaluating the accuracy of forecasting, the research enhances the understanding of tourism demand dynamics. Furthermore, this study assesses the effects of the COVID-19 pandemic on three types of tourism demand, namely religious, business, and VFR, in order to estimate the extent of their response to the crisis. Overall, this chapter has provided a comprehensive overview of prior literature, highlighted the significant contributions of the thesis, and clearly outlined the objectives and methodologies of the study. By examining various facets of tourism demand, this research significantly advances knowledge in the field.

CHAPTER 4: METHODOLOGY

4.1. Introduction

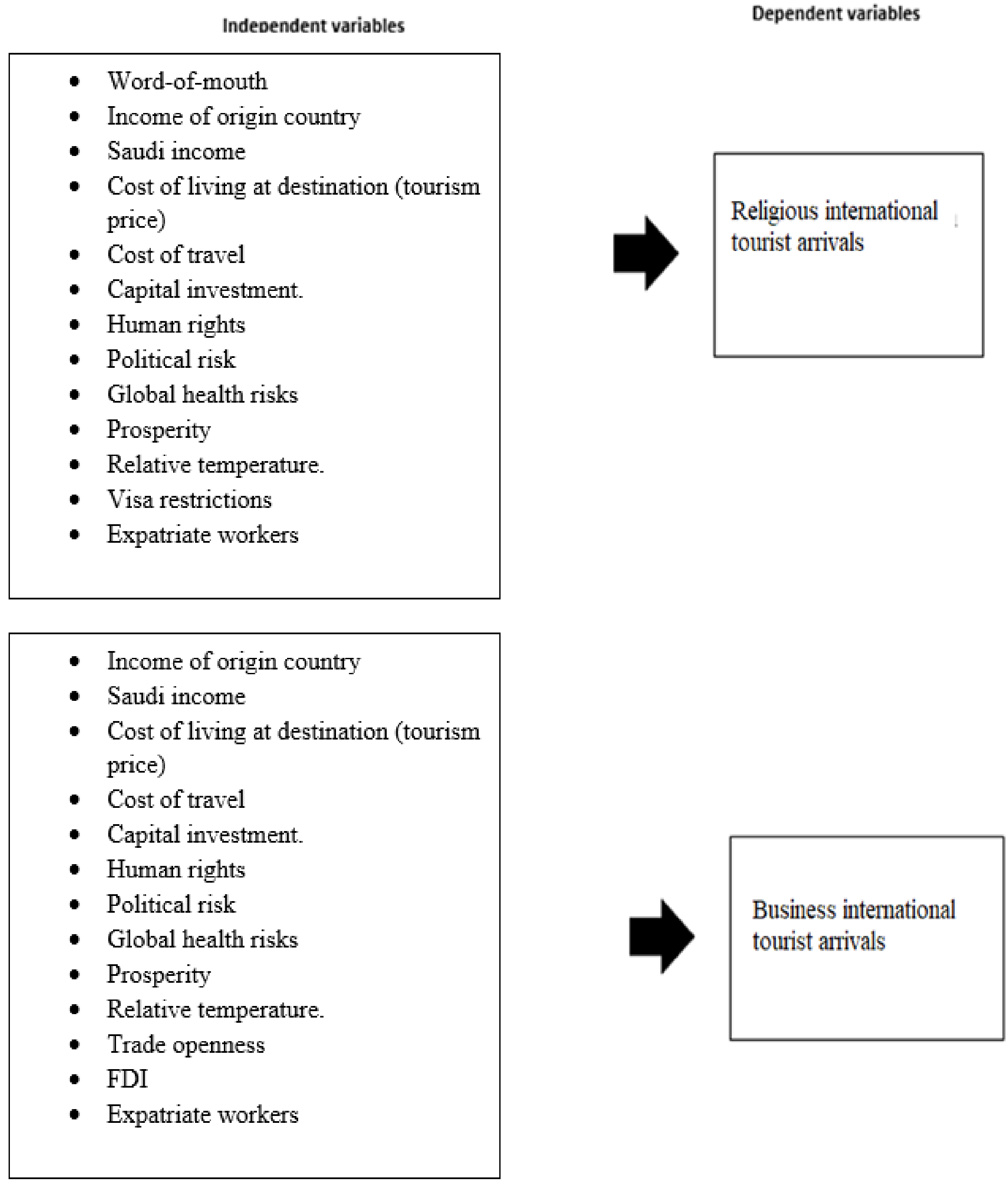
Chapter three provided the study's literature review and theoretical and conceptual frameworks. This chapter introduces the research design that was used to test the hypotheses developed from the conceptual model proposed for this study. This chapter provides an overview of the methodology that was chosen based on the research aim and objectives. It presents the research design, empirical model, operation and measurement of variables, data collection tools, and data collection procedures. This research sought to analyse the factors affecting the international tourism demand in Saudi Arabia. The econometric quantitative approach applied the gravity model and data from the period 2000 to 2019.

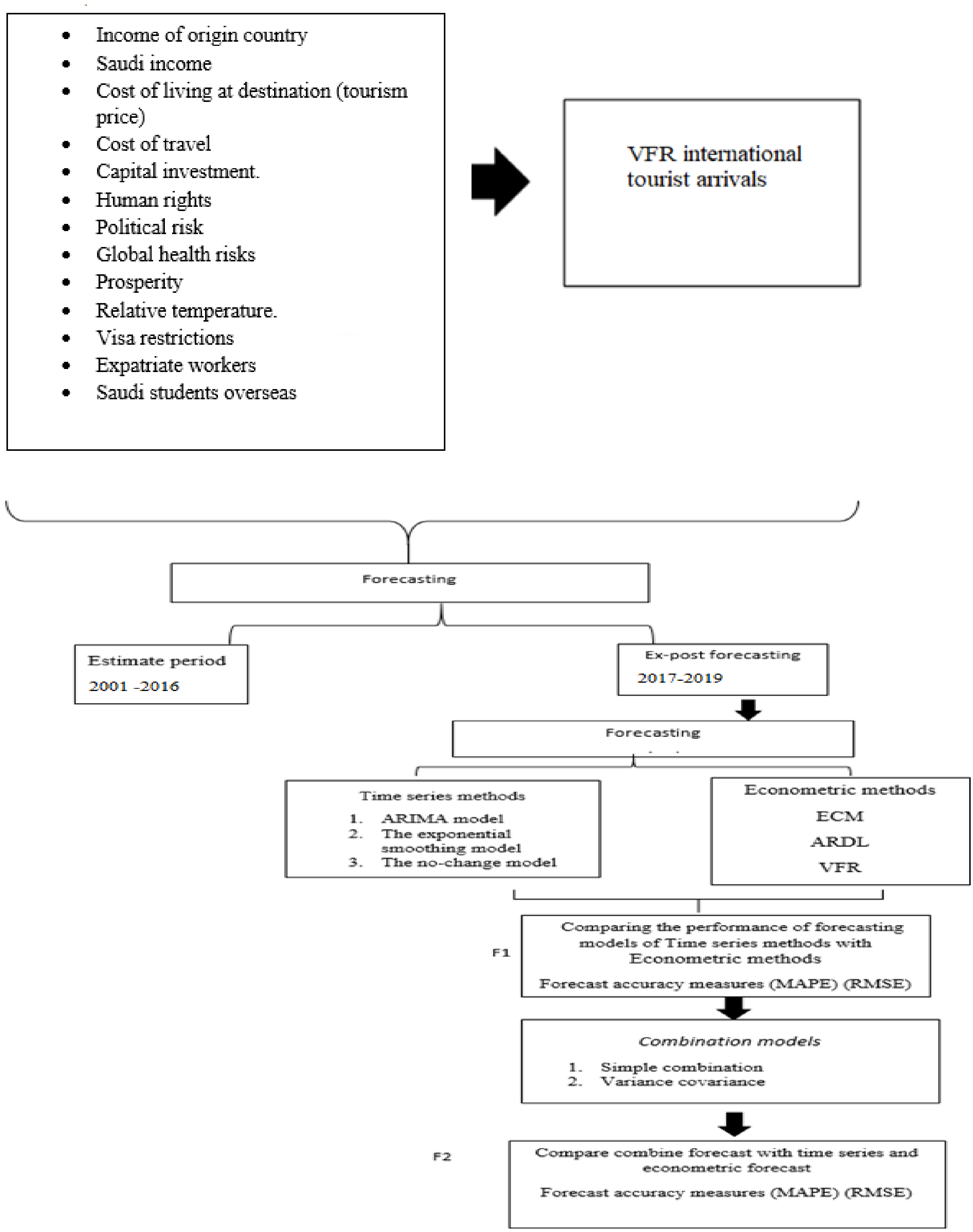
This chapter is structured as follows. Section 4.2 outlines the study's conceptual framework, Section 4.3 introduces the research design, followed by the model specifications in Section 4.4. Section 4.5 presents the research methodology and variables measurement, and Section 4.6 the data analysis. Section 4.7 concludes the chapter.

4.2. The study conceptual framework

The researcher constructed her own conceptual framework for this study, taking into account variables where data were available and using variables derived from the theoretical and empirical literature on tourism demand. A diagrammatic representation of the relationship between the research variables is presented in Figure 4.1.

Figure 4.1. The study's conceptual framework





In the conceptual framework of this study, it was proposed that modern econometric methods be used to identify the significant determinants of tourism demand in Saudi Arabia based on the purpose of the visit. Additionally, the study forecasts international tourism demand for Saudi Arabia using time series methods, econometric methods, and combination forecast methods to evaluate and compare the forecasting performance in the context of international tourism demand. This study used the number of tourists arriving in Saudi based on the purpose of visit as a measurement of international tourism demand (dependent variable).

The main (dependent) variables for the study were the number of religious, business and VFR international tourist arrivals to Saudi Arabia, as supported by previous studies. The factors influencing international tourism demand in Saudi Arabia were derived from a review of the literature having been empirically shown to be significantly influencing international tourism demand. The factors considered in the study were economic variables: the income of both origin country and destination, cost of living at destination, travel costs, investment in tourism, FDI, and trade openness; and non-economic factors: political risk, human rights, word-of-mouth, health risks, relative temperature, destination prosperity, expatriate workers, international Saudi students, and dummy variable (including health risks and Hajj incidents). Several past studies have been reviewed and it was evident that the objectives of this current research are only partly addressed in previous literature. Neither the impact of non-economic variables on tourism demand, nor purpose of visit, have been adequately examined in past studies.

Based on the studies reviewed in Chapter three, it is evident that increasing the income of the origin country leads to the increased ability of tourists to travel overseas, and the increased income of the destination country leads to enhancing its capacity to provide the necessary services and infrastructure.

The cost of living (also known as the relative price) is often considered in tourism demand modelling. This is the cost of goods and services consumed by tourists in the destination country. Travel cost is also an important determinant of international tourism demand, as tourists move from their origin country to the destination, often by air transportation, the most popular type of international travel. The costs associated with tourism demand make up a large portion of the expenditure associated with tourism. Therefore, as evident in the literature, the increased cost of transport and price negatively affects tourism demand.

A destination's reputation is often spread by word-of-mouth. It is likely that recommendations from previous travellers to a particular destination can have a greater impact on prospective travellers than advertising efforts in brochures. People welcome input from those with first-hand knowledge of a destination. This is a lagged dependent variable and has been found to have positive significant impact on tourism demand.

Trade and FDI significantly impact business tourist inflows into a country. FDI can lead to increased tourism demand since foreign investors provide the tourism capacity that the country lacks. This might be achieved by building more hotels and tourism attractions (including theme parks) and improving transport facilities. As a result, the country is stimulated or able to accommodate a larger number of visitors (Craigwell & Moore, 2008; Kumar et al., 2022; Tang et al., 2007).

Business tourists are another link between FDI and tourism. Business tourists are entrepreneurs and managers from other countries who visit several tourist destinations in order to look for investments and promote and sustain business in the host country (Selvanathan et al., 2012). An increase in FDI could lead to a cyclical effect on investigative business travel (Tang et al., 2007). Business trips abroad often occur in connection with selling products to the destination country or purchasing products from that country. It is likely that an increase in trade activity between the origin and destination countries will stimulate the demand for imports and exports, resulting in a growth in business tourism between these two countries. Open markets increase opportunities for international trade, which in turn increases the volume of business tourism. Business tourism is generated by the expansion of international trade and the expansion of air transportation, as well as the easing of visa requirements. Moreover, capital investments in tourism play a significant role in creating attractive destinations and delivering tourism services smoothly. As noted earlier, investing in tourism can result in the development of appropriate tourist accommodations and restaurant or catering services, the establishment of affordable and reliable transportation services, and the improvement of tour guide operations. Furthermore, other investments aim to support the tourism industry, such as the establishment of ICT, logistics, finance, and marketing firms. These investments can also develop human resource capacity, with employees working in the front offices of tourism-related businesses.

Non-economic factors, including security, political risks, visa requirements, health risks, prosperity, and weather, may also have a significant influence on tourism demand. Due to increasing globalisation, most countries are interconnected with other countries via various means. For instance, in the context of Saudi Arabia, foreign expatriates are working in the kingdom, while Saudi residents are studying abroad. Saudi students studying abroad are expected to positively affect VFR tourism, while foreign expatriate workers are expected to positively affect all types of tourism demand under consideration in this study (religious, business and VFR). Additionally, the literature indicates that sharing a common language and religion between bilateral countries may attract more tourists. The ability to communicate in a common language makes information about tourist destinations more accessible to tourists, reducing barriers to communication with local residents and providing a sense of security throughout the trip. Tourism demand may also be influenced by religious ties. Sharing a common religion between countries results in a shared set of values and understanding of national taboos, as well as a decrease in conflict between tourists and locals.

The study has sought to provide more accurate forecasting models of tourism demand using various methods. Modern econometric (ECM, ARDL and VFR) and time-series models (ARIMA, Naïve or no change and exponential smoothing) were used to generate individual forecasts and then two combination forecast method (Simple Average and Variance– Covariance combinations) were created (as discussed in Chapter three). A comparison of the performance of the various models and forecasts was also conducted. The research objectives have been transformed into testable hypotheses. The conceptual framework for the study is presented in Figure 4.1.

4.3. Research philosophy, research design paradigm and strategy

Choosing the appropriate research philosophy is related to the researcher's understanding of their own ontology, epistemology, and axiology. This study relies on the philosophy of positivist research. Positivist researchers believe that reality can be examined and observed objectively. Positivists believe that data collecting could occur in the community and is connected to people and their ideas (Levin, 1988). Its main methods are scanning techniques and often include statistical analysis (Creswell et al., 2007). Positivists tend to present their results in a more generalised and deductive manner. In positivist research, a hypothesis is first proposed, which is then tested using the data collected. The hypothesis can then be tested empirically, and if it is tested using the collected data and accepted, it is proved. Based on facts and data, this method of study is primarily objective (Hesse-Biber, 2010). Positivism was considered appropriate for this study because it allowed for a deductive method and the development of hypotheses that could be tested with empirical facts.

The positivist approach was used in this study to measure the effect of causal relationships and correlation between study variables. Formulating research in variables and assumptions using quantitative tools (statistical tests) so there is no relationship between the researcher and the research community, ensures that the researcher is objective. The researcher aims in this approach to prove or deny a specific hypothesis, given that the sample in this type of scientific method is random, so that the results of the study can be generalised (Creswell et al., 2003). Ontologically, this current research is an objective study because it has particular objectives and hypotheses, employs deductive logic through examining a hypothesis derived from a particular study aim, and analyses the results using data collected from secondary sources. This is quantitative secondary research. According to Bryman (2015), a quantitative approach is used if the data are measurable and quantifiable.

4.4. Model specification

This study employed a gravity model approach to modelling tourism demand. This considered that tourist flows between two regions/countries were directly proportional to the countries' economic size (measured in terms of GDP or GDP per capita) and inversely proportional to the distance between them (mainly measured in travel costs).

The base gravity model formula is as follows:

$$F_{ijt} = G\frac{M_{it}\ M_{jt}}{D_{ij}} \qquad \text{Equation (4.1)}$$

Where F_{ijt} *is* the tourist flows from origin country i to destination country j at time t. M_i and M_j are the economic size factors in i and j countries, D_{ij} is the geographical distance between i and j countries and G *is the gravitational constant.* Both β_1 and β_2 were expected to be positive, and is β_3 was expected to be negative .

It is noted that in the base gravity model, the interpretation of tourism flows depended on three variables represented by the size of the economy of the country under study, the economy size of the origin country (partner) expressed in GDP per capita, and the geographic distance between them.

The basic gravity model was augmented by incorporating additional variables that enhance or reduce flows, including a set of physical–geographical factors or social, political, or semi-economic factors, cultural similarities, language similarities, historical connections and trade relations between the origin and destination that might have direct and indirect influences on the flows (Ulucak et al., 2020). The coefficients of determination of empirical gravity model estimations are often high, indicating that it is a useful tool for analysing bilateral tourism flows.

The augmented model's most widely used form, developed independently by Tinbergen (1963) and Pöyhönen (1963), explains bilateral trade between two countries.

$$F_{ij} = \beta_0 M_i^{\beta_1} M_j^{\beta_2} D_{ij}^{\beta_3} V_{ij}^{\beta_4}$$

Equation (4.2)

Where V_{ij} is an additional factor that either promotes (e.g., membership in a trading bloc, shared cultural background) or constrains (e.g., tariffs, adjustment costs), or other social, political, or semi-economic factors between i and j countries.

Based on the tourism demand theory and gravity models discussed widely in the literature review, augmented factors are: Saudi Arabian income, and the income of the origin country, the cost of travel and cost of living at the destination, trade openness, and FDI, investment in tourism in the destination, human rights index, political risks, visa restrictions, relative temperature, the country's prosperity, global health risks, and Saudi international students.

Standard gravity models typically employ panel data models. These may provide additional insights by capturing key correlations through time and reduce the risk of selecting an unrepresentative year. Furthermore, panels enable the monitoring of unobservable specific effects between trading partners. Thus, in order to evaluate the effects of gravitational variables on tourist inflows, the panel gravity model framework was used in the study. The estimation process used annual data from the major origin countries for religious, business and VFR tourism demand from 2000 to 2019.

Empirical results from these studies were interpreted in terms of demand elasticity, which can be defined as the change in the quantity of tourism demand with respect to the change in each of the determinants of tourism demand. It is assumed that in the case of elasticity greater than one, that is, when demand is elastic, the demand for tourism services will respond proportionately more than the change in the independent variable. In contrast, an elasticity lower than one, which is an inelastic demand, implies that a change in tourism services responds proportionally more slowly than a change in the explanatory variables. It was expected that most goods and services would have a positive income elasticity of demand. Basic goods and services should be income inelastic, whereas luxury items should be income elastic. In this study, as in most of the previous empirical literature (Barry & O'Hagan, 1972; Fourie et al., 2020; Saha et al., 2017; Witt & Martin, 1987), the tourism demand model adopted the double-logarithmic form because this provides two main advantages: the estimated coefficients can be interpreted as demand elasticity, and the double-logarithmic form has a relatively low residual variance comparison to other functional forms of the same datasets (Jud & Joseph, 1974). However, political risks, human rights, global health risks, and destination prosperity, were not transformed into logarithmic forms because they are indexes, and their interpretation makes sense without the logarithm. The analysis was conducted using a statistical analysis package (EViews 11 software).

To estimate tourism demand for Saudi Arabia, five models were developed, discussed as follows.

- **Model 1:** Estimate GMM model for religious tourism demand

Model 1 incorporated the following variables: lagged dependent variable, income of origin country, income of destination country, cost of living at the destination, cost of travel, capital investment at the destination, political risks at the destination, human rights of the destination, relative temperature, prosperity index, global health risks, and visa restrictions.

The augmented version of the gravity model considered for religious tourism demand estimation is given as follows:

$$LNRT_{ijt} = \beta_0 + \beta_1 lnRT_{ijt-1} + \beta_2 IO_{ijt} + \beta_3 ID_{it} + \beta_4 lnP_{it} + \beta_5 LnCT_{ijt} + \beta_6 LnINVEST_{it} + \beta_7 PRISK_{it} + \beta_8 LnHI_{it} + \beta_9 TEM_{it} + \beta_{10} Ln_{PIit\ it} + \beta_{11} LnHR_{it} + \beta_{12} DHAJ_i + \beta_{13} DVRi + \mu_i + T_i + \varepsilon_{ijt} \qquad \text{Equation (4.3)}$$

Where $LNRT_{ijt}$ is the number of international arrivals to destination j (Saudi Arabia) from origin countries i (21 origin countries) at time t. Annual data from 21 origin countries for 2000 to 2019 (except for destination prosperity data, which was only available from 2009) was considered in the estimation process. The dimensions of this model are 21 countries for 20 years. The countries considered in the empirical analysis were Pakistan, India, Indonesia, Jordan, Egypt, Iraq, Bangladesh, Morocco, Sudan, Bahrain, Oman, UAE, Turkey, Algeria, Malaysia, Kuwait, Iran, Nigeria, Afghanistan, UK, and Tunisia. These source countries were considered because, according to the Saudi Tourism Information and Research Centre (MAS), they represent more than 85 percent of the total number of international tourist arrivals in the study period. The period of study (2000 to 2019) was selected because the data on tourist flows based on the purpose of visit was unavailable for the periods before 2000 and after 2019.

- **Model 2**: ARDL model for business tourism demand

Model 2 incorporated the following variables: income of origin country, income of destination country, cost of living at the destination, cost of travel, capital investment at the destination, FDI, trade openness, political risks at the destination, human rights of the destination, relative temperature, prosperity index, and global health risks. The ARDL model could be written as:

Long-run equation:

$$lnBT_{ij,t}=\gamma_0+\gamma_1 \text{lnIO}_{i,t}+\gamma_2\text{lnID}_{j,t}+\gamma_3\text{lnP}_{ji,t}+\gamma_4\text{lnCT}_{ij,t}+\gamma_5\text{INVEST}_{j,t}+\gamma_6\text{TADE}_{ij,t}+\gamma_7\text{lnFDI}_{ij,t}+\gamma_8\text{PRISK}_{j,t}+ \gamma_9\ \text{HI}_{j,t}+\ \gamma_{10}ln\text{TEM}_{ij,t}+\ \gamma_{11}\text{PI}_{j,t}+\ \gamma_{12}\text{HR}_{t}\quad +\varepsilon_{ij,t} \qquad \text{Equation (4.4)}$$

Where LnBT_{it}= the dependent variable, which is the number of business tourist arrivals from origin countries to Saudi Arabia.

Error correction term:

$$ECT_{ij,t-1}=\text{lnBT}_{ij,t-1}-\gamma_1\text{lnIO}_{i,t-1}-\gamma_2\text{lnID}_{j,t-1}-\gamma_3\text{lnP}_{ji,t-1}-\gamma_4\text{lnCT}_{ij,t-1}-\gamma_5\text{INVEST}_{j,t-1}-\gamma_6\text{TADE}_{ijt-1,}-\gamma_7\text{lnFDI}_{ij,t-1}-\gamma_8\text{PRISK}_{j,t-1}-\gamma_9\ \text{HI}_{j,t-1}-\ \gamma_{10}ln\text{TEM}_{ij,t-1}-\gamma_{11}\text{PI}_{j,t-1}-\gamma_{12}\text{HR}_{t-1} \qquad \text{Equation (4.5)}$$

Short-run dynamic model:

$$\Delta lnBT_{ij,t}=\beta_0+\sum_{k=0}^{q_1}\beta_1\Delta\text{lnIO}_{i,t-k}+\sum_{k=0}^{q_2}\beta_2\ \Delta_{\text{t-k}}\text{lnID}_{j,t-k}+\sum_{k=0}^{q_3}\beta_3\ \Delta\ \text{lnP}_{ij,\text{t-k}} +\sum_{k=0}^{q_4}\beta_4\Delta\ \text{ln}CT_{ij,t-k}+\sum_{k=0}^{q_5}\beta_5\ \ \Delta\ \text{INVEST}_{j,t-k}+\sum_{k=0}^{q_6}\beta_6\text{ln}\Delta\ \text{TADE}_{ij,t-k}+\sum_{k=0}^{q_7}\beta_7\Delta\ \text{lnFDI}_{ij,t-k}+ \sum_{k=0}^{q_8}\beta_8\Delta\ \ \text{PRISK}_{j,t-k}+\ \ \sum_{k=0}^{q_9}\beta_9\ \Delta\ HI_{j,\text{t-k}}\ +\ \sum_{k=0}^{q_{10}}\beta_{10}\ \Delta\ \text{lnTEM}_{ij,t-k}\ +\ \sum_{k=0}^{q_{11}}\beta_{11}\Delta\ \ \text{PI}_{j,t-k}+ \sum_{k=0}^{q_{12}}\beta_{12}\ \Delta\ \text{HR}_{t-k}+\varepsilon_{ijt}+\ \ \mu ECT_{i,j,t-1} \qquad \text{Equation (4.6)}$$

The ARDL model is used to estimate the short and long relationship. While the short-term effect can be estimated by inferring the sizes of coefficients of the differenced variables, the long-term effect can be estimated by the lagged explanatory variables.

Where Δ is the difference operator, i is the country of origin, j refers to destination country and t is time (2000-2019), T and K denote the cross-section and time dimensions respectively, and ε_t is the white noise error term. The coefficient from $\gamma_1$to γ_{12}represents the long-term relationship between the variables, while the coefficient β_1 to β_{12} with the summation signs depict the short-term dynamics of the variables.

When long-run relationships between variables were found, an ECM was applied to estimate the short-term effect adjustment speed of explained variables to independent variables.

$ECT_{ij,t-1}$ denotes the adjustment speed of the equilibrium relationship from short-run dynamics through explanatory variables. μ is the coefficient of the speed adjustment, this coefficient is normally a statistically significant negative sign, and this coefficient of the error correction term (λ) indicates the extent to which the deviation from the long-run equilibrium in the previous time period (t-1) is being adjusted in the current time period (t). A negative and statistically significant λ implies convergence of the variables to the long-run equilibrium (Nkoro & Uko, 2016).

Saudi Arabia's inbound business tourism was estimated using data from 11 major origin countries between 2000 and 2019. According to the MAS, these countries represent more than 80 percent of the total number of business international tourist arrivals in the study period. Although countries like Hong Kong, the Philippines and China are major markets of business tourism to Saudi Arabia, their data was not available for the study period and many years are missing. For these reasons, they were excluded from this study. The sample consisted of countries from lower-income economies (Sudan), lower-middle-income economies (India, Bangladesh, Indonesia, Pakistan and Egypt), high-income economies (UK, Kuwait, and US), and upper-middle-income economies (Jordan and Turkey).

- **Model 3**: ARDL model for VFR tourism demand

This model incorporated the following variables: income of origin country, income of destination country, cost of living at the destination, cost of travel, capital investment at the destination, political risks at the destination, human rights of the destination, relative temperature, prosperity index, global health risks, Saudi international students, and visa restrictions.

The variables in VFR tourism demand were cointegrated and thus they could proceed with estimating the long-run coefficients using the ARDL model which will take the following form:

Long-run equation :

$\mathrm{lnVFR}_{ij,t}=\gamma_0+\gamma_1\mathrm{lnIO}_{i,t}+\gamma_2\mathrm{lnID}_{j,t}+\gamma_3\mathrm{lnP}_{ij,t}+\gamma_4\mathrm{lnCT}_{ij,t}+\gamma_5\mathrm{INVEST}_{j,t}+\gamma_{6ij,t}+\gamma_6\mathrm{lnOVESTU}_{ijt}+\gamma_7\mathrm{PRISK}_{j,t}+\gamma_8\ \mathrm{HI}_{j,t}+\ \gamma_9 ln\mathrm{TEM}_{ij,t}+\ \gamma_{10}\mathrm{PI}_{j,t}+\ \gamma_{11}\mathrm{HR}_t\ +\varepsilon_{ijt}$ Equation (4.7)

Where lnVFR denotes the number of VFR international tourist arrivals to destination (Saudi Arabia) from origin countries at time t (2000 to 2019).

Error correction term :

$ECT_{ijt-1}=\mathrm{lnVRF}_{ij,t-1}-\gamma_1\mathrm{lnIO}_{i,t-1}-\gamma_2\mathrm{lnID}_{j,t}-\gamma_3\mathrm{lnP}_{ji,t-1}-\gamma_4\mathrm{lnCT}_{ij,t-1}-\gamma_5\mathrm{INVEST}_{j,t-1}-\gamma_6\mathrm{lnOVESTU}_{ji,t-1,}-\gamma_7\ \mathrm{PRISK}_{j,t-1}-\gamma_8\ \mathrm{HI}_{j,t-1}-\ \gamma_9 ln\mathrm{TEM}_{ij,t-1}-\gamma_{10}\mathrm{PI}_{j,t-1}-\gamma_{11}\mathrm{HR}_{t-1}$ Equation (4.8)

Short-run dynamic model:

$\Delta\ \mathrm{lnVRF}_{ij,t}=\beta_0+\sum_{k=0}^{q_1}\beta_1\Delta\ \mathrm{lnIO}_{i,t-k}+\sum_{k=0}^{q_2}\beta_2\ \Delta\ \mathrm{lnID}_{j,t-k}+\sum_{k=0}^{q_3}\beta_3\ \Delta\ \mathrm{lnP}_{ij,t-k}+\ \sum_{k=0}^{q_4}\beta_4\Delta\ \mathrm{ln}CT_{ij,t-k}+\ \sum_{k=0}^{q_5}\beta_5\ \Delta\ \mathrm{INVEST}_{j,t-k}\ +\ \sum_{k=0}^{q_6}\beta_6\mathrm{ln}\Delta\mathrm{OVESTU}_{ij,t-k}+\sum_{k=0}^{q_7}\beta_7\Delta\ \ \mathrm{PRISK}_{j,t-k}+\ \sum_{k=0}^{q_8}\beta_8\ \Delta\ \mathrm{HI}_{j,t-k}\ +\ \sum_{k=0}^{q_9}\beta_9\ \Delta\ \mathrm{lnTEM}_{ij,t-k}\ +\sum_{k=0}^{q_{10}}\beta_{10}\ \Delta\ \mathrm{PI}_{j,t-k}\ +\sum_{k=0}^{q_{11}}\beta_{11}\ \Delta\ \mathrm{HR}_{t-k}+\varepsilon_{ij,t}+\mu ECT_{ij,t-1}$ Equation (4.9)

The variables in VFR tourism demand were cointegrated and thus could proceed with estimating the long-run coefficients using the ARDL model, which took the following form:

Long-run equation:

$\ln VFR_{ij,t}=\gamma_0+\gamma_1 \ln IO_{i,t}+\gamma_2 \ln ID_{j,t}+\gamma_3 \ln P_{ij,t}+\gamma_4 \ln CT_{ij,t}+\gamma_5 INVEST_{j,t}+\gamma_{6ij,t}+\gamma_6 \ln OVESTU_{ijt}+\gamma_7 PRISK_{j,t}+$
$\gamma_8\ HI_{j,t}+\ \gamma_9 ln TEM_{ij,t}+\ \gamma_{10} PI_{j,t}+\ \gamma_{11} HR_t\ +\varepsilon_{ijt}$ Equation (4.10)

Where lnVFR denotes the number of VFR international tourist arrivals to destination (Saudi Arabia) from origin countries at time t (2000 to 2019).

Error correction term:

$ECT_{ijt-1}=\ln VRF_{ij,t-1-}\ \gamma_1 \ln IO_{i,t-1}-\gamma_2 \ln ID_{j,t}-\gamma_3 \ln P_{ji,t-1}-\gamma_4 \ln CT_{ij,t-1}-\gamma_5 INVEST_{j,t-1}-\gamma_6 \ln OVESTU_{ji,t-1,}-\gamma_7$
$PRISK_{j,t-1}-\gamma_8\ HI_{j,t-1}-\ \gamma_9 ln TEM_{ij,t-1}-\gamma_{10} PI_{j,t-1}-\gamma_{11} HR_{t-1}$ Equation (4.11)

Short-run dynamic model:

$\Delta \ln VRF_{ij,t}=\beta_0+\sum_{k=0}^{q_1}\beta_1\Delta \ln IO_{i,t-k}+\sum_{k=0}^{q_2}\beta_2\,\Delta \ln ID_{j,t-k}+\sum_{k=0}^{q_3}\beta_3\,\Delta \ln P_{ij,t-k}+\ \sum_{k=0}^{q_4}\beta_4\Delta \ln CT_{ij,t-k}$
$+\ \sum_{k=0}^{q_5}\beta_5\,\Delta\ INVEST_{j,t-k}+\sum_{k=0}^{q_6}\beta_6 \ln\Delta OVESTU_{ij,t-k}+\sum_{k=0}^{q_7}\beta_7\Delta\ PRISK_{j,t-k}+\sum_{k=0}^{q_8}\beta_8\,\Delta\, HI_{j,t-k}\ +$
$\sum_{k=0}^{q_9}\beta_9\,\Delta \ln TEM_{ij,t-k}+\sum_{k=0}^{q_{10}}\beta_{10}\,\Delta\, PI_{j,t-k}+\sum_{k=0}^{q_{11}}\beta_{11}\ \Delta\ HR_{t-k}+\varepsilon_{ij,t}+\mu ECT_{ij,t-1}$ Equation (4.12)

An ECM was estimated to illustrate the short-run dynamics of the model in the form of the lagged differences of the variables and an error correction term ECT_{t-1} representing the speed of the variables adjusting to the long-run equilibrium.

The data on VFR inbound tourist arrivals in Saudi Arabia was obtained from 15 major source markets. According to the MAS, these countries represent about 90 percent of VFR international tourist arrivals in the average study period. The primary source countries chosen are Kuwait, UAE, Pakistan, India, Indonesia, Jordan, Egypt, Iraq, Bangladesh, Sudan, Bahrain, Turkey, Malaysia, Algeria and Qatar. The data period of the study was from 2000 to 2019. Saudi Arabia is among the GCC countries, as well as Bahrain, Kuwait, Oman, Qatar, and the UAE. They share significant economic, cultural, and religious relationships. GCC citizens are allowed to visit Saudi Arabia without a visa under the GCC agreement. Large numbers of migrant labourers from countries such as Pakistan, India, Indonesia, Jordan, Egypt, Iraq, Bangladesh, Sudan, and Turkey work in Saudi Arabia and they are eligible to bring their dependents to Saudi Arabia under the Saudi visa regime.

- **Model 4**: ARDL model for aggregate tourism demand

This model incorporated the following variables: income of origin country, income of destination country, cost of living at the destination, cost of travel, capital investment at the destination, the political risks at the destination, human rights of the destination, relative temperature, prosperity index, global health risks, the number of students studying abroad, FDI, and trade openness.

The variables in tourism demand were cointegrated and thus could proceed with estimating the long-run coefficients using the ARDL model, which took the following form:

Long run equation:

$$\mathrm{lnAGT}_{ij,t} = \gamma_0 + \gamma_1 \mathrm{lnIO}_{i,t} + \gamma_2 \mathrm{lnID}_{j,t} + \gamma_3 \mathrm{lnP}_{ji,t} + \gamma_4 \mathrm{lnCT}_{ij,t} + \gamma_5 \mathrm{INVEST}_{j,t} + \gamma_6 \mathrm{TADE}_{ij,t} + \gamma_7 \mathrm{lnFDI}_{ij,t} + \gamma_8 \mathrm{PRISK}_{j,t} + \gamma_9 \mathrm{HI}_{j,t} + \gamma_{10} ln\mathrm{TEM}_{ij,t} + \gamma_{11} \mathrm{PI}_{j,t} + \gamma_{12} \mathrm{HR}_t + \gamma_{13} \mathrm{lnOVESTU}_{ji,t-1} + \varepsilon_{ijt} \qquad \text{Equation (4.13)}$$

Where lnAGT denotes a dependent variable that is the number of aggregate international tourist arrivals to Saudi Arabia.

Error correction term:

$$ECT_{ijt-1} = \mathrm{lnAGT}_{ij,t-1} - \gamma_1 \mathrm{lnIO}_{i,t-1} - \gamma_2 \mathrm{lnID}_{j,t-1} - \gamma_3 \mathrm{lnP}_{ji,t-1} - \gamma_4 \mathrm{lnCT}_{ij,t-1} - \gamma_5 \mathrm{INVEST}_{j,t-1} - \gamma_6 \mathrm{TADE}_{ijT-1,} - \gamma_{7\mathrm{lnFDI}_{ij,t-1}} - \mathrm{PRISK}_{j,t-1} - \gamma_9 \mathrm{HI}_{j,t-1} - \gamma_{10} ln\mathrm{TEM}_{ij,t-1} - \gamma_{11} \mathrm{PI}_{j,t-1} - \gamma_{12} \mathrm{HR}_{t-1} - \gamma_{13} \mathrm{OVESTU}_{ij,t-1} \qquad \text{Equation 4.(14)}$$

Short-run dynamic model:

$$\Delta\mathrm{ln\ AGT}_{ij,t} = \beta_0 + \sum_{k=0}^{q_1} \beta_1 \Delta\mathrm{lnIO}_{\ i,t-k} + \sum_{k=0}^{q_2} \beta_2 \Delta\ \mathrm{lnID}_{j,t-k} + \sum_{k=0}^{q_3} \beta_3 \Delta\ \mathrm{lnP}_{ij,t-k} + \sum_{K=0}^{q_4} \beta_4 \Delta\ CT_{ij,t-k} + \sum_{k=0}^{q_5} \beta_5 \mathrm{ln}\Delta\ \ \mathrm{INVEST}_{j,t-k} + \sum_{k=0}^{q_6} \beta_6 \mathrm{ln}\Delta\mathrm{TADE}_{ij,t-k} + \sum_{k=0}^{q_7} \beta_7 \Delta\ \mathrm{FDI}_{ij,t-k} + \sum_{k=0}^{q_8} \beta_8 \Delta\ \mathrm{PRISK}_{j,t-k} + \sum_{k=0}^{q_9} \beta_9 \Delta\ \mathrm{HI}_{j,t-k} + \sum_{k=0}^{q_{10}} \beta_{10} \Delta\ \mathrm{TEM}_{ij,t-k} + \sum_{k=0}^{q_{11}} \beta_{11} \Delta\mathrm{PI}_{j,t-k} + \sum_{k=0}^{q_{12}} \beta_{12}\ \Delta\ \mathrm{HR}_{t-k} + \sum_{k=0}^{q_{13}} \beta_{13} \mathrm{ln}\Delta\mathrm{OVESTU}_{ij,t-k} + \varepsilon_{ijt} + \mu ECT_{i,j,t-1} \qquad \text{Equation(4.15)}$$

An ECM was estimated to illustrate the short-run dynamics of the model in the form of the lagged differences of the variables and an error correction term ECT_{t-1} representing the speed of the variables adjusting to the long-run equilibrium.

In the aggregate tourism demand model, the sample included 14 origin countries (Kuwait, UAE, Bahrain, Pakistan, India, Indonesia, Jordan, Egypt, US, Bangladesh, Sudan, Malaysia, Algeria and Qatar). These countries were selected because they accounted for up to 80 percent of total tourism arrivals to Saudi Arabia, according to the MAS, over the study period from 2000 to 2019.

- **Model 5**: ARDL model for expatriate workers

This model was estimated for comparison purposes and incorporated the variables: Saudi Arabian income, income of origin country, cost of travel, and expatriate workers.

The variables were cointegrated and thus could proceed with estimating the long-run coefficients using the ARDL model, which took the following form:

$\ln TA_{ij,t} = \gamma_0 + \gamma_1 \ln IO_{i,t} + \gamma_2 \ln ID_{j,t} + \gamma_3 \ln CT_{ij,t} + \gamma_4 \ln EXPWOR_{ji,t} + \varepsilon_{ij,t}$ Equation (4.16)

Where lnTE denotes the number of international tourist arrivals to Saudi Arabia (total number, religious, business and VFR). The optimal lag length was found to be one, based on the AIC model selection criterion.

Error correction term:

$ECT_{ij,t-1} = \ln ATA_{ij,t-1} - \gamma_1 \ln IO_{i,t-1} - \gamma_2 \ln ID_{j,t-1} - \gamma_3 \ln CT_{ij,t-1} - \gamma_4 \ln EXPWOR_{ij,t-1}$ Equation (4.17)

Short-run dynamic model:

$\Delta \ln TA_{ij,t} = \beta_0 + \sum_{k=0}^{q_1} \beta_1 \Delta \ln IO_{i,t-k} + \sum_{k=0}^{q_2} \beta_2 \Delta \ln ID_{j,t-k} + \sum_{k=0}^{q_3} \beta_3 \Delta CT_{ij,t-k} + \sum_{k=0}^{q_4} \alpha_{4i} \Delta \ln EXPWOR_{ij,t-k} + \varepsilon_{ij,t} + \mu ECT_{ij,t-k}$ Equation (4.18)

An ECM was estimated to illustrate the short-run dynamics of the model in the form of the lagged differences of the variables and an error correction term ECT_{t-1} representing the speed of the variables adjusting to the long-run equilibrium. t= time from 2000 to 2019; j =destination (Saudi Arabia).

The expatriate workers sample came from eight countries (Pakistan, Indonesia, India, Egypt, Bangladesh, Jordan, Iraq, and Sudan).

4.5. Methodology

Using panel data has several advantages over cross-sectional or time series analysis in this case. The literature on tourism demand suggests that heterogeneity among source countries is evident in tourism demand and needs to be considered (Dogru et al., 2021; Dogru et al., 2017). Panel data techniques help avoid misspecification of the model and biased outcomes (Baltagi, 2021; Hsiao, 2014). Furthermore, as Hsiao (2014) stated, panel data techniques produce more informative data with greater variability and less collinearity. Additionally, employing the panel data technique significantly improves the generalisability of empirical findings (Kim & Lee, 2017).

The panel data approach is a more robust technique for modelling tourism demand for Saudi Arabia when appropriate data are available. A panel data approach consists of a cross-section of data (countries) over a number of periods. The conjunction of time series and cross-sectional data increases the degree of freedom in the estimation process, provides additional information, reduces the problems associated with multicollinearity and autocorrelation, and enables dynamic specification. The accuracy of the estimated parameters can therefore be improved by using panel data analysis (Garin-Munoz & Montero-Martín, 2007; Habibi & Abbasianejad, 2011; Khalid, Okafor, & Aziz, 2020; Li et al., 2017; Viljoen et al., 2019).

Two primary methods are used for estimating panel data models: static and dynamic. Both methods have been applied to analyse tourism demand in the literature. In existing studies, static panel data models, including pooled, random, or FE models, have been used to analyse panel data (Garin-Munoz & Amaral, 2000; Görmüş & Göçer, 2010; Seetaram & Dwyer, 2009). The tourism demand literature was dominated by static regression until the beginning of the 1990s.

However, the static approach suffers from various statistical problems, including spurious regression, because it assumes all the variables are stationary. From the literature, it has been demonstrated that most of the data regarding tourism demand, income, and prices, are non-stationary variables. Consequently, the mean is not zero and the variance is infinite. Due to the violation of the estimator's assumptions, it does not produce reliable estimates and regression tends to be spurious (Witt & Martin, 1987; Witt & Witt, 1995). There are limitations to the FE model, including its inability to estimate time-invariant variables. Moreover, heteroscedasticity and serial correlation may significantly affect the efficiency of the estimates in the FE model. In spite of the fact that the random effects (RE) model allows for the estimation of time-invariant variables, by assuming the error term to be random, the RE estimator could lead to bias in the results because of covariance between the error term and the explanatory variable.

The use of static panel data models when modelling tourism demand is not optimal because these models fail to capture the effects of dynamic mechanisms underlying panel data. In most cases, macroeconomic data contain relationships that are dependent on time as well as the past values of another macroeconomic indicator. A static panel data model cannot take into account the dynamic nature of the data. This leads to estimates that are in violation of the major Gauss–Markov assumptions, thus not being BLUE (best, linear, and unbiased).

In contrast to these major shortcomings, dynamic panel data models overcome these issues by incorporating the lagged dependent variable into the model, allowing the estimation of long-run tourism demand elasticities. A growing interest in dynamic panel data models in tourism economics literature has emerged in recent years as a result of the limitations of static panel data models. The use of dynamic panel data models has become the predominant empirical approach for modelling tourism demand in recent years (Brida & Risso, 2009; Dogru et al., 2017; Falk, 2010; Li et al., 2017; Pham et al., 2017).

To estimate tourism demand models, the extant studies have primarily used the GMM estimator of the Arellano-Bond approach. As a dynamic panel data model, this model can be useful for modelling tourism demand. Although GMM does have some limitations, it might not be the most suitable model in some contexts. GMM estimation of Arellano–Bond and Arellano–Bover techniques in panels with larger time series (T) than units (N) can lead to over identification of parameter estimates (Roodman, 2009a). Also, when estimating the long-run relationships, the GMM estimators assume that the study variables move together in the long run, which is not always the case. Prior to estimating long-run coefficients, a cointegration test is necessary to determine whether the study variables move together over time. Dynamic models are advantageous since they provide both short-run and long-run elasticities. A further advantage of dynamic panel models is they solve the non-stationarity problem, this provides confidence in the reported coefficients and standard errors (Garin-Munoz & Montero-Martín, 2007).

This study used two dynamic regression models to explain the factors affecting Saudi Arabia's international tourism demand. A dynamic GMM panel regression model was used to analyse the effect of the factors on religious international tourism demand for Saudi Arabia, since cross-sectional data (21 countries) are large than the time series (20) data. In contrast, ARDL panel data regression models were used to determine the effect of the factors on other types of tourism demand under investigation (business, VFR, aggregated, and expatriate worker models), because the time series of these models is large than the cross-sectional data i (T>N).

Even though the selected estimators in this study are the GMM-DIFF and ARDL, for comparison purposes and to check the validity of the small panel data of the unit root test, the results of the static model also display.

4.5.1. Preliminary tests in panel data models

There is a need to conduct preliminary tests in tourism demand studies in order to determine the nature of the panel data to be used in the panel data modelling process. The use of panel data models when modelling tourism demand can produce spurious coefficient estimates if the presence of cross-sectional dependence and unit root is not taken into account (Alawin & Abu-Lila, 2016; Bai & Kao, 2006; Baltagi, 2005, 2021; Pesaran, 2006; Pesaran & Yamagata, 2008).

First, the error term might contain unobservable common factors, and the error term might be correlated with its past values, the explanatory variables and the past values of the explanatory variables. Estimation of tourism demand models based on panel data exhibiting cross-sectional dependence may result in biased results if the appropriate panel data model is not used. Second, slope coefficients might need to be estimated separately for the member of the panel. Consequently, producing a single slope coefficient will be asymptotically biased when slope heterogeneity exists. Third, when the panel data probability distribution does not follow a stochastic process, tourism demand models that are estimated without considering the stationarity of the study variables will produce biased estimates, especially when long-run estimates are being modelled. In order to generate asymptotically unbiased, efficient, and consistent estimates, these preliminary tests must be conducted.

4.5.1.1. Cross-sectional dependence

The first step in panel data models is to determine if the error terms have a cross-sectional dependence. Cross-sectional dependence indicates that an observed or unobserved shock in one unit impacts other units in the panel. Common stocks such as macroeconomic, technological, legal, political, environmental, and health shocks can cause cross-sectional dependence. Thus, these common factors are likely to be present in cross-sectional economic data (Andrews, 2005). Some specific shocks can impact all countries (cross-section unit) in similar or different ways. In both cases, the errors may exhibit undesirable cross-sectional dependence. For instance, the global recession may have a higher impact on the per capita income of some countries than on others. Terrorist attacks in a particular year might have a significant and varied impact on tourist arrivals from all source countries. To put it differently, the interdependence between the unobserved elements, such as the error term and the regressors, indicates that panel members are cross-sectional dependent, leading to biased and inconsistent results. Furthermore, the Monte Carlo experiments conducted by Pesaran (2006) showed evidence that excluding the probability of cross-sectional dependence causes a significant bias in the estimated models. Although alternative methods for testing the existence of cross-sectional dependence have been developed, the CD test, CD Lagrange multiplier (CD_{lm}) test of Pesaran et al. (2004), and the adjusted Lagrange multiplier (LM_{adj}) test of Pesaran and Yamagata (2008) have been the most commonly used and efficient methods (Dogru et al., 2021). When the cross-sectional dimension of the panel (N) is high, the CD and CD_{lm} tests of Pesaran et al. (2004) can generate efficient estimates, and the LM_{adj} test of Pesaran et al. (2008) produces efficient outcomes for panels with both large cross-sectional dimensions and long-time series.

The cross-sectional dependence CD test, CD Lagrange multiplier (CD_{lm}) test and the adjusted Lagrange multiplier (LM_{adj}) test can be used in the context of large N and small T, producing efficient estimates. In contrast, the Breusch and Pagan (1980) test is used for cross-sectional dependence in the context of large T and small N. The Breusch-Pagan LM test is run with the null of cross-sectional independence in the regression model's residuals. If the resulting test statistical Probability is less than five percent, implying that the null of cross-sectional independence is strongly rejected, the LM_{adj} of Pesaran and Yamagata (2008) generates efficient results for panels for large cross-sectional dimensions and long-time series.

4.5.1.2. Slope heterogeneity

Researchers must also test for slope heterogeneity when modelling tourism demand via panel data models, in addition to testing for cross-sectional dependence. Slope heterogeneity implies that the slope coefficients in a panel dataset may not be homogeneous across cross-sectional units. The assumption of homogeneous slope coefficients may obscure panel members' unit-specific characteristics (Menyah et al., 2014). Pesaran and Yamagata (2008) developed the most widely recognised methods for determining slope homogeneity. They produced two test statistics for the slope homogeneity test, labelled as $\hat{\Delta}$ and $\hat{\Delta}_{adj}$. In their analysis, Pesaran and Yamagata (2008) found evidence from Monte Carlo simulations that the $\hat{\Delta}_{adj}$slope homogeneity test indicates better small sample properties. Null hypothesis of the test is: “slope coefficients are homogenous”.

4.5.1.3. Panel unit root tests

The existence of a unit root is likely to generate weak instruments in variable issues in the mode. Baltagi (2005), and Gujarati and Porter (2009) argued that a variable is stationary at a level if its mean and variance remains constant over time, and the covariance value between the two time points depends on the gap or distance or lag between the two time periods, not on the actual time when the covariance is estimated. Panel unit root tests often have greater power than root unit time series tests, since unit root tests use cross-sectional data (Levin et al., 2002).

There are several assumptions in which a panel unit root test can be categorised. To begin with, there are first- and second-generation panel tests. First generation panel unit root tests suppose cross-sections are independent. These include the Levin-Lin-Chu (LLC) test (Levin et al., 2002), the Im-Pesaran-Shin (IPS, 1997), and the Fisher type test (Choi, 2001; Maddala & Wu, 1999). Nevertheless, the literature indicates that cross-sectional dependency is more likely to occur as a result of unobserved common factors or macroeconomic shocks. Recently, second generation panel unit root tests, including Breitung and Das (2005), and Moon and Perron (2004), have enhanced the first generation by allowing for cross-sectional dependence for all variables (Bangake & Eggoh, 2010). Panel unit root tests can be categorised according to the homogeneity or heterogeneity of the autoregressive coefficient (Levin et al., 2002). Some panel unit root tests assume a common unit root specification across countries, but this assumption is potentially restrictive (Levin et al., 2002). This assumption is employed by the LLC (2002), as well as the Breitung (2001) and Hadri (2000) tests. The other form of root unit tests accepts the heterogeneity in the autoregressive coefficient; therefore, these tests assume individual unit root processes. Such tests are much less restrictive and more efficient. These tests are proposed by IPS (1997), Maddala and Wu (1999), and Choi (2001).

In addition, most panel root unit tests, including the LLC, IPS, Brest, Harris-Tzavalist (HT) (1999) and Maddala and Wu (MW) tests, have a null hypothesis that the panel data have a unit root against the alternative hypothesis that of panel data have no unit root. . The three tests, LLC, IPS, and Fisher, are based on test statistics that have a limiting normal distribution, since N and T tend to ∞, and the T approach to ∞ appears to be adequately faster than N. Furthermore, the HT, Breitung and Hadri tests consider the case where N tends to ∞ and T is fixed (De Blander & Dhaene, 2012).

Finally, the unit root tests of the panel can be classified according to a correction for autocorrelation. The Breitung, Fisher, augmented Dickey-Fuller (ADF), and IPS tests apply regression on lagged difference terms to deal with autocorrelation and correct it. Other techniques, including Fisher PP, HT, and Hadri, use kernel weighting techniques to estimate the long-term variance as an alternative approach. The LLC test employs both approaches of autocorrelation correction. In this study, to examine the stationarity of the variables in the models, six panel unit root tests were performed: LLC, HT, IPS, Fisher type test using ADF and PP, and Breitung tests.

4.5.1.4. Panel cointegration test

Cointegration tests and long-run relationships can be conducted after considering the unit root test, since the variables under investigation are integrated of order one or non-stationary. The presence of a cointegration between the variables may indicate the presence of a long-run relationship between the variables. Estimation analysis can then be conducted because using time series data with unit roots may led to unreliable analysis. The cointegration mechanism can be used to address this problem without sacrificing the long-term equilibrium relationship if one exists. Cointegration refers to the equilibrium relationship between variables in the long run. An error correction mechanism forces the short-run deviation from equilibrium in one period to move towards equilibrium in the next period. Economic theory states that international tourism demand is dependent on income, relative prices and transport prices, as well as other variables. In the short term, the variables might move apart but in the long term, they move together. When those variables are individually non-stationary, but their linear combination (residuals) is stationary, they could be cointegrated. Economic theory does not inform whether the variables have a stochastic trend or not and if the trends are common between variables, thus, to investigate these issues, cointegration tests are required after unit root checks (Lim & McAleer, 2001).

Therefore, this study employed panel cointegration testing using Kao (1999) and Pedroni (1999, 2004) to determine whether cointegration exists between these non-stationary variables. The Kao (1999) cointegration test is only performed on homogeneous panels, whereas the Pedroni (1999, 2004) test can be performed on both homogeneous and heterogeneous panels. These tests have been widely used in empirical studies in recent years to investigate the cointegrating relationships between variables in a model.

While cointegration technology is becoming increasingly common in the literature, the main problem is the low power of these tests when applied to short-time data. The bundling of cross-sectional data and time-series data therefore enables a greater degree of freedom and improves the power of the cointegration test (Pedroni, 1999). The null hypothesis of these tests states that there is no cointegration between the series. The alternative hypothesis states that there is cointegration between the series.

The Pedroni cointegration test was used to demonstrate the effects of both in-section (within) and cross-section (between) in the panel. These tests were grouped into two distinct categories. In the first category, four tests were pooled within the dimension, while in the second category, three tests were pooled within the dimension. The proposed within test statistics employed were: The panel PP-statistics, panel v-statistics, panel rho-statistics, and panel ADF-statistics. The proposed between test statistics employed were: group PP-statistics, group rho-statistics, and group ADF-statistics. Another cointegration test used in this study is the Kao (1999) cointegration test. This test utilises Dickey-Fuller (DF) and ADF tests as cointegration tests for panel data analysis.

4.5.2. Panel model estimation

As mentioned earlier, two primary methods are used to estimate panel data models: static and dynamic. These models are explained in the next sections.

4.5.2.1. Static panel regression estimators

The main econometric methods to estimate panel data for tourism demand are pooled ordinary least squares (POLS), FE, and RE models. When all variables in the study are stationary at the level POLS regression models, FE models, and RE panel data models can be used (Hsiao, 2014; Song, Witt, & Li, 2003). These produce different assumptions about the intercept term. The intercept remains constant along with all cross-sectional entities in the POLS model; in the RE model the intercept varies randomly across cross-sectional entities; and in the FE model, the intercept varies between cross-sectional entities so that each unit has a fixed intercept. In other words, as suggested by Greene (2003, 2008), a POLS regression model can be used if z_i only contains a constant term. If z_i contains unobserved variables and is correlated with x_{it}, the FE model should be used, whereas the RE model should be used if unit effects differ across cross-sectional units. To decide which of these models was best to use in the analysis, three tests were applied: the Chow test (Chow, 1960) for differentiation between the POLS and FE model; the LM test (Breusch & Pagan, 1980) to choose between POLS and RE; and the Hausman (1978) test to determine whether a FE or RE panel data model is appropriate for a given situation.

4.5.2.2. Dynamic panel regression model

Both the GMM-DIFF and ARDL estimator models are discussed in this section.

The generalised method of moments (GMM)

In order to statistically test the hypotheses of this study, a regression analysis estimator was utilised. As discussed in the literature review section, the GMM estimator is often used in tourism panel literature. Compared to other regression analysis estimators, the GMM is less biased and more efficient. The GMM estimator was introduced by Arellano and Bond (1991).

The panel data contained cross-sectional data covering 21 origin countries, and economic and non-economic factors that influence religious inbound tourism demand in Saudi Arabia across the period 2000 to 2019. The dynamic panel regression model consisted of a lagged dependent variable to measure the word-of-mouth effect and repeat visits. Tourism demand is inherently dynamic, as a tourist's previous visit experience may influence potential tourism demand through repeat visitation and/or word-of-mouth. Past tourism demand, also recognised as an autoregressive word or lagged dependent variable, is a significant determinant of tourism demand. It is a stylistic assumption in the literature on tourism demand that when tourism demand models are calibrated, the lagged dependent variable captures a huge amount of information (Song & Li, 2008). To be more specific, lagged dependent variables capture word-of-mouth influence, repeat visitation, habit persistence and destination-related supply factors such as hotel development (Dogru et al., 2017; Song et al., 2019). From an econometrics perspective, the dynamic panel data model is practical since it takes into account the impact of past values of dependent variables. Accounting for the influence of the past values of dependent variables in the tourism demand model context is a critical component of the theoretical model since it illustrates tourists' intentions to return to the destination and/or to recommend the destination to their friends and relatives.

The model could not be estimated by POLS methods due to the small number of observations in the time dimension (T). Therefore, the GMM difference given in Arellano and Bond (1991) was considered for estimation. As discussed in studies by Baltagi (2021), Barman and Nath (2019), and Lam and Shiu (2010), the advantages of using the GMM method are: avoiding biased and inconsistent estimates and endogeneity problems due to POLS estimation; and transforming the original regression by differencing the variables that eliminate the country-specific FE and unit root issues. This method uses a lagged independent variable and independent variables as instruments in the estimation. However, as with any method, the panel GMM difference approach has its limitations. The first limitation is weak instrumental variables (IV) in the Diff-GMM model. Since variables lagged by T periods (T = 1, 2...) are utilised as IV, the correlation between the IV and the endogenous variable is weak when T is large. Weak IV may result in poor performance with limited samples (in practice, relatively small). When evaluating regressions, the lag periods of the IV must be limited rather than using all previous lags to alleviate the weak IV issue. The second limitation is if the dependent variable is persistent and close to being a random walk; the use of the difference GMM estimator leads to both a biased and inefficient estimate of infinite samples (when T is small) if the dependent variable is persistent and close to being a random walk. The third limitation is being unable to obtain the estimates of time-invariant factors such as distance, common language, contiguity, or colonial ties.

Estimated coefficients are short-run elasticities. Long-run elasticities could be obtained by dividing each coefficient by (1-b1). Therefore, one of the advantages of employing a dynamic model is that we can obtain both short-run and long-run elasticities. An important assumption for the validity of GMM is that the instruments are exogenous. Therefore, testing for the validity of instruments is an important aspect of testing the statistical properties of this model This requires testing for first-order as well as second-order autocorrelations in the error term. In order to test for first-order and second-order serial correlation, two diagnostics are computed using the Arellano and Bond tests to check the absence of autocorrelation in the residuals of the model. The hypothesis is that there is no second-order serial correlation. It is a special feature of dynamic panel data GMM estimation that the number of moment conditions increases with T. In order to evaluate the over-identification restrictions, a Sargan test is conducted (Roodman, 2009a, 2009b)

Autoregressive distributed lag (ARDL)

In addition to the GMM model, this study used the ARDL model proposed by Pesaran et al. (2001) and Pesaran et al. (1999) to analyses business, VFR, and expatriate worker tourism demand models. In light of the fact that the panel sample included more years than the cross-sample, it was understood that the variables might not be stationary, but I(1) and the model were likely to be dynamic. In cases in which the variables under consideration are suffering from the unit root, a cointegration approach or differentiating the series according to integration order is suggested. The model offers a unique method for estimating the short-term and long-term dynamics of a model containing a mixture of variables I(0) and I(1). The most significant advantage of ARDL is the independence from broader parameters such as the number of endogenous and exogenous variables to be used, the number of optimal lags, the number of optimal lags for different variables, and the model's ability to function even with a small number of observations (Duasa, 2007). The model also provides robust results for small samples in addition to addressing endogeneity (Kakar et al., 2010). Furthermore, the ARDL procedure allows for testing of cointegration between a dependent variable and a set of independent variables regardless of integration order. Nevertheless, the procedure cannot be used when the variables are I (2) (De Vita & Abbott, 2002).

In addition to the cointegration tests of Kao (1999) and Pedroni (2004), the coefficient of the error correction term was used to decide if a cointegration relationship existed between the study variables. A negative and statistically significant coefficient of the error correction term indicates the existence of a cointegration relationship between the study variables, and thus the estimated model's outcomes can be interpreted, as the estimated model is asymptotically unbiased, effective, and accurate. The ARDL test is effective because it allows for a sufficient number of lags and is more effective for limited sample data sizes (Laurenceson & Chai, 2003; Pesaran et al., 1999).

The ARDL cointegration approach requires two stages to estimate. The first stage is to examine the existence of a long relationship between all variables. When there is a long-term relationship between variables (cointegration), the second step is to estimate the coefficient via the ARDL model.

4.5.3. Research data and sources of data

The study used secondary annual data from 2000 to 2019, selected mainly on the basis of data availability. Through using annual data, problems and issues caused by seasonality can be avoided. These data for the study were obtained at the national level from various sources, as shown in the Table 4.1. As indicated, earlier in the chapter, the analysis was conducted using EViews 11 software.

4.5.4. Variables measurement

As noted previously, the demand for a tourism product in the destination (Saudi Arabia) by tourists from the origin country could be impacted by a range of factors. This includes the income of the origin country, the income of the destination country, cost of living in the destination, travel costs, capital investment in the tourism sector, trade openness, FDI, expatriate workers, Saudi international students, respect for human rights, political risks, temperature, visa restrictions, prosperity, and global health risks.

4.5.4.1. Dependent variable

The dependent variable of this empirical study is the natural log of the number of international tourist arrivals from each country of origin to Saudi Arabia in the period from 2000 to 2019. In this study, tourism demand was measured in four different ways: total international tourist arrivals; religious arrivals; VFR arrivals; and business arrivals. Although there are numerous ways of measuring tourism demand, such as tourism expenditure and overnight stays, the number of arrivals is the most commonly used measure. As a key objective of this study was to compare results based on the purpose of the visit, the researcher estimated an aggregate model based on the total international tourist arrivals. Disaggregate models based on the purpose of the trip (religious, VFR, and business tourists) were estimated using their respective dependent variables. Most studies, including Barman and Nath (2019), Fourie et al. (2020), Martins et al. (2017), and Shaheen (2019), have used the number of tourist arrivals as the dependent variable in the model of tourism demand. Others, including Aslan (2016), Cárdenas-García et al. (2015), Gholipour and Tajaddini (2018, 2019), and Song et al. (2010), employed tourist expenditure in the destination country as the dependent variable. For Saudi Arabia, data on the number of tourists from other countries is available. However, there is no data on the expenditure of tourists by origin country in Saudi Arabia. Considering Saudi Arabia's government has recently announced a new initiative to increase the annual number of tourists, this makes this research even more important. The data on the number of tourists was taken from the publications of the MAS.

4.5.4.2. Explanatory variables

Word-of-mouth effect

This study uses word-of-mouth (a lagged dependent variable) as the explanatory variable. Numerous studies have incorporated lagged dependent variables into demand models to measure word-of-mouth or habit persistence on tourism demand (Afonso-Rodríguez, 2017; Barman & Nath, 2019; Garin-Munoz & Montero-Martín, 2007; Garín-Muñoz & Montero-Martín, 2007; Habibi, 2017; Rani & Zaman, 2020; Song, Witt, & Li, 2003; Buigut et al., 2015; Fourie & Santana-Gallego, 2013; Garín-Mun, 2006; Garin-Munoz & Montero-Martín, 2007; Ghaderi et al., 2017; Habibi, 2017; Khadaroo & Seetanah, 2008;

Mendieta-Aragón & Garín-Muñoz, 2020). This variable was obtained by lagging the number of international tourist arrivals variable for one period.

Income

Although there are several proxies to measure income, including nominal GDP, real GDP, Gross national product (GNP), or per capita, national disposable income (NDI), per capita disposable income and industrial production index, and per capita private consumption, in this study income is measured using per capita GDP as a measure of output for the overall economy. It is calculated by dividing a country's GDP by the number of its population. The GDP per capita variable has been commonly utilised as a proxy for income (economic size) in international tourism demand literature (Adeola et al., 2018; Adeola & Evans, 2020; Barman & Nath, 2019; Fourie et al., 2020; Ghalia et al., 2019; Hanafiah & Harun, 2010; Lim, 1997a; Martins et al., 2017; Morley et al., 2014; Park et al., 2019; Peng et al., 2014; Peng et al., 2015; Permatasari & Esquivias, 2020; Petrovic & Milićević, 2019; Rosselló et al., 2020; Song & Lin 2010; Viljoen et al., 2019). Previous studies have used GDP per capita in the destination and origin countries (Altaf, 2021; Eilat & Einav, 2004; Kaplan & Aktas, 2016; Kumar et al., 2020; Rosselló et al., 2020; Rosselló et al., 2017). This current study used GDP per capita at constant prices (2000=100) for both the origin and the destination countries to measure the economic size (income) based on the gravity model, economic demand theory. Data were collected from the World Development Indicators (WDI) and the World Bank online resources.

Cost of living at the destination (tourism price)

Another critical factor of the tourism demand model is tourism price. The exchange rate influences the cost of living in the destination country, which should be considered in modelling tourism demand. The inclusion of exchange rates as a separate variable in the model may lead to a multicollinearity problem (Dogru & Sirakaya-Turk, 2018). Therefore, in this current study, the price variable used was the CPI of the destination country divided by the CPI of the origin country, adjusted by the exchange rate between the destination country and origin country currency. This followed the method of a number of theoretical and empirical studies (Habibi & Abbasianejad, 2011; Song et al., 2019; Viljoen et al., 2019).

It is defined as follows:

$$p_{it} = \frac{CPI_{SAt}}{CPI_{it}} * \frac{EX_{SAt}}{EX_{it}} \qquad \text{Equation (4.19)}$$

Where ($p_{i,t}$) denotes relative price, CPI_{KSAt} and CPI_{it} represent CPI of destination country and origin country, respectively; EX_{SAt} and EX_{it} are the exchange rates of local currency to the dollar at year t for Saudi Arabia and tourist country of origin, respectively.

The study extracted the data related to CPI from the International Monetary Fund (IMF) and exchange rates from International Financial Statistics (IFS).

Travel costs

As discussed in Chapter three, this study measured travel cost by multiplying the geographic distance with the crude oil price, following the work of Jong et al. (2020), as shown in Equation (20).

$TCiit = Distiit * Crude\ oil\ pricet$ Equation (4.20)

Where $TCiit$ denotes the travel cost from destination to origin countries, and $Distiit$ is the distance (kilometres) between the destination and the country of origin multiplied by the crude oil price. Average oil prices were collected from the Statistical Review of World Energy. The study extracted data related to the distance variable from the French Centre d'Etudes Prospectives et d'Informations Internationals (CEPII).

Capital investment in travel and tourism.

The Saudi government has invested in a variety of tourism infrastructures and attractions, such as historical sites, museums, and theme parks, to attract tourists from around the world. Multi-billion-dollar headline investment plans have been established for accommodation, hotel rooms, furnished flats, transport, and the service industries. As noted in Chapter two, mega-projects such as Neom, Qiddiyah and the development project for Al-Diriyah are expected to attract tourists in large numbers. The government has taken steps to make it easier for individuals to visit the country, including improving the visa process (Alotaibi, 2021). The data on capital investment in travel and tourism were taken from the WTTC, measured in billion USD (real prices). The data collection method was also used by Jeje (2021).

Trade openness

As countries have adopted trade policies based on economic openness and trade liberalisation, travel rates have increased, which has stimulated the flow of business tourists between countries (Ibrahim, 2013). This study includes the trade openness variable since arrivals for business purposes is consistently the second-largest tourism market in Saudi Arabia. That is why the volume of trade is assumed to influence demand for travel to Saudi Arabia and is thus included in the model used to explain business demand. Trade openness is used as an indicator of the volume of international trade between the destination and the country of origin of the tourist. This variable is included in studies by Gholipour and Foroughi (2019), Gholipour, Tajaddini, et al. (2021), Habibi et al. (2009), Ibrahim (2013), Kulendran and Wilson (2000a), Kulendran and Witt (2003a), Smith and Toms (1978), Turner et al. (1998), and Turner and Witt (2001).This study measured trade openness as the total amount of import and export of goods and services between Saudi and the country of origin, divided by the GDP of Saudi Arabia, a method used by Eilat and Einav, 2004, and Phakdisoth and Kim, 2007. This was calculated as follows:

$$TO_{ijt} = \left(\frac{EXP_{j,it} + IM_{j,it}}{GDP_{j,t} + GDP_{it}}\right) *100 \qquad \text{Equation (4.21)}$$

Where EXP_{ji} is the volume of exports of Saudi Arabia to the country of origin; IM_{ji} is the volume of imports in Saudi Arabia from each origin tourist at the time t. GDP_i and GDP_j are per capita in tourist countries and destination, respectively, in current international dollars. The data for trade openness were collected from the World Bank direction of trade statistics, and the IMF.

FDI

Saudi Arabia aims to attract greater foreign investment, with Vision 2030 presenting important foreign investment opportunities in the fields of education, housing, energy, health and tourism. Additionally, the government aims to attract FDI into sectors such as entertainment, which has great potential for the future. The kingdom plans to expand FDI from 3.8 percent to 5.7 percent, which is the global average. In general, FDI provides host countries with a wealth of skills and advantages (Aluko, 2020), which, in the case of Saudi Arabia, include managerial skills, technical skills, new job opportunities, capacity building, and establishing a competitive environment to diversify non-oil exports in order to fulfil Vision 2030.

FDI was measured by FDI inflow as a percentage of GDP. FDI data were extracted from the World Bank's WDI database, as used by other researchers (Craigwell & Moore, 2008; Fereidouni & Al-Mulali, 2014; Gholipour & Foroughi, 2019, 2020; Samargandi et al., 2022; Selvanathan et al., 2012; Tang et al., 2007).

Saudi international students

The Saudi scholarship program, known as the King Abdullah Scholarship Program (KASP), is perhaps one of the world's largest national scholarship programs in higher education. The aim of the program is to send Saudi men and women to universities abroad, to train and develop Saudi human resources in the fields of labour market and scientific research. This will assist Saudi Arabia in becoming more competitive and to offer essential support to Saudi institutions, both public and private (Hilal et al., 2015). The KASP was introduced in 2005 and the program has formalised Saudi students' long-term and already robust outward movement to universities throughout the world. Saudi students are travelling to countries like the US, UK, Canada, and Australia; to continental European countries such as the Netherlands, Germany, and Italy; and to many Asian countries, including China, India, Malaysia, Singapore, South Korea, and Japan. Moreover, many Saudi students study in neighbouring Arab countries, including Egypt, Lebanon and Jordan. The resulting growth in international graduate student numbers makes Saudi Arabia an ideal study context for this topic. This variable is measured by the total number of overseas Saudi students studying out of the country, as a proxy for Saudi international students, to determine the influence they have on VFR tourism demand. Data were obtained from the Saudi Statistics Centre and Saudi Ministry of Education.

Human rights

The human rights issue in Saudi Arabia is a major concern. As noted in previous chapters, internationally, Saudi Arabia has been criticised for its human rights record. As stated in the United Nations Human Rights Indicators (UN Human Rights Office, 2012), human rights are legal guarantees that protect individuals and groups from any act or omission that constitutes an interference with their basic freedoms, entitlements, and human dignity.

To measure human rights variable , CIRI+CIRIGHTS human rights score was used as a proxy to measure Saudi Arabia's human rights in this study. A high score on human rights indicates that all 14 human rights are respected in that country, while the low score indicates low respect for human rights. Data were sourced from the CIRI+CIRIGHTS Data Project, which provides indices for the level of government respect for various internationally recognised human rights. Each country obtains an aggregate human rights score based on a weighted average of the 14 indicators measuring various aspects of human rights. These datasets cover categories such as women's rights, civil and political liberties, freedom of speech and the press, worker's rights (including acceptable conditions of work with respect to minimum wages, hours of work, and occupational safety and health), and physical integrity rights (protections from extra-judicial killing, disappearance, torture, and arbitrary and political detention).

Political risks

This study used the political risk index as a proxy to capture the political environment in the destination country. This index is published in the International Country Risk Guide (ICRG), which is widely used in economic research. It is a comprehensive proxy, which measures more than political instability. As an oil-exporting country, Saudi Arabia has had many conflicts with neighbouring countries (Ekiz et al., 2017). The political risk index has 12 variables (government stability, socio-economic conditions, investment profile, internal conflicts, external conflicts, corruption, military in politics, religious tensions, law and order, ethnic tensions, democratic accountability, and quality of the bureaucracy). This study used total points of all 12 components. This index was rescaled for ease of explanation, following the work of Yap and Saha (2013). The minimum score is zero, meaning a very stable country, and the maximum score is 100, meaning a very unstable country (i.e., with high political risks).

Relative temperature

Among Saudi Arabia's opportunities and challenges in attracting tourists is climate. Saudi Arabia has an abundance of deserts, hills, mountains, and terrains with forests, cities, and beautiful seas (Almohmmad, 2021). Taylor and Ortiz (2009) measured climate by the temperature and sunny hours.

Kulendran and Dwyer (2012) measured the maximum temperature, relative humidity and sunshine hours. Ridderstaat et al. (2014) used rainfall, temperature, wind speed, and cloud coverage.

In the tourism demand literature, either the destination's climate or the origin country's climate are included in the tourism demand models. However, there is a scarcity of studies that take the climate of both the source and destination countries into account. But the climatic conditions in both the origin and the destination countries should be properly considered when modelling tourism demand (Kulendran & Dwyer, 2012; Lorde et al., 2016). Fourie and Santana-Gallego (2013), and Li et al. (2017) used climate difference between home and destination in their analysis.

This study used the ratio between the origin country's temperature and the destination country's temperature as a proxy of relative temperature.

Expatriate workers

Saudi Arabia has 10.5 million expatriate workers, accounting for roughly a third of the kingdom's population (Balli, Ghassan, et al., 2019). Thus, this study used the expatriate workers variable to explain tourism inflows to Saudi Arabia. This variable was measured using the number of expatriates (foreign workers) in Saudi Arabia from origin countries, as conducted in previous studies, including Balli et al. (2018), Balli et al. (2016), and Balli, Ghassan, et al. (2019), which used the number of immigrants. Seetaram (2012) used the number of Australian residents born overseas. The data for expatriate workers were collected from the collected from the United Nations' Immigration Database

The prosperity of the destination

Saudi Arabia's prosperity is crucial to the tourism industry, as it provides a conducive environment for tourism, contributes to the development of new tourist destinations and activities, and provides employment opportunities that contribute to the tourism industry's growth. This study used the Legatum Prosperity Index's data to examine the specific effect the prosperity of the destination has on the magnitude of tourist demand. The Index was developed by the Legatum Institute with the objective of highlighting the strengths and weaknesses of each country, so that economic decisions could be made about how to build more inclusive societies and open economies and empower people with the tools they need to drive prosperity.

As the Legatum Prosperity Index grows in popularity, prosperity is projected to gain substantial traction. This index is predicated on the premise that prosperity takes on multiple dimensions. Economic and social wellness encompasses all facets of human existence, including but not limited to emotional well-being and life satisfaction. Similarly, wealth exceeds the physical stock of capital to include qualitative characteristics that are not quantifiable in monetary terms (Amin & Siddiq, 2019).

To calculate a country's overall prosperity Index score, an average of the twelve pillars of prosperity is taken. (Pillars are safety and security, personal freedom, governance, social capital, investment environment, entrepreneurial conditions, infrastructure and market access, economic quality, living conditions, education, health, and natural environment). This measurement was also adopted by Fereidouni et al. (2013), Youssef and Diab (2021), and Sokhanvar et al. (2018) in their economic studies.

Global health risks

In general, previous studies have examined the relationship between infectious diseases and tourism demand within a particular country or region. For instance, Kuo et al. (2008), McAleer et al. (2010), Blake et al. (2003), Cooper (2006), and Zeng et al. (2005) used dummy variables or the number of infected/dead to measure global health risks. However, recent studies in tourism demand, including Karabulut et al. (2020) and Kocak et al. (2022), used a newly developed indicator: the WUPI. This was developed by Ahir et al. (2020) to investigate the effect of pandemic uncertainties and global pandemics on tourism demand.

This study uses the WUPI. The Index is calculated by counting the frequency of the word 'uncertainty' and its variants appearing near a word related to pandemics in the Economist Intelligence Unit nation reports multiplied by 1,000. A large number indicates greater uncertainty about pandemics. The WUPI data is available as frequencies, but these were converted in this study to annual observations by taking the average to achieve consistency with the datasets for other variables.

Dummy variable

Previous studies have used dummy variables to capture the impact of a specific event on tourism demand. For example, as noted in Chapter three, Lee (2005), Veloce (2004), Habibi et al. (2009), and Khoshnevis Yazdi and Khanalizadeh (2017), used a range of dummy variables (e.g., the 1991 Gulf crisis, SARS and 11 September 2011).

This study included three dummy variables: visa restrictions, the hajj incident and cultural affinity, as discussed below.

Visa restrictions

This study examines the impact of visa restrictions on international tourist demand flow in Saudi Arabia. Cheng (2012), and Czaika and Neumayer (2017) used dummy variables to investigate the impact of visa requirements on tourism demand. The variable takes number 1 if visitors from origin countries require a visa, otherwise it takes 0.

The Hajj incident

In the context of religious tourism, the Hajj stampede incident of September 2015 due to overcrowding may have had a negative impact on religious tourism. In this study, the Hajj incident was used as a dummy variable, taking number 1 in 2015 and 2016, otherwise taking 0.

Cultural affinity

In order to measure cultural affinity, several different proxies can be used, such as linguistic and religious similarities. In gravity models, these variables are considered extensively. Yang and Zhang (2019) for example, examined the effects of cultural distance on bilateral tourism movements and concluded that cultural distance negatively and significantly influences international tourist flows. In this respect, Fourie et al. (2015) estimated that religious similarity has a significant positive influence on inbound tourism.

In the current analysis, religious and language similarity between the host and the home country was used as a proxy for cultural affinity. Saudi Arabia's official language is Arabic, although English is widely spoken as well. Islam is the state religion of Saudi Arabia. Therefore, cultural affinity is measured as a percentage of citizens in tourist origin countries classifying their adherence to Islam and who speak Arabic. This was represented by data calculated from variables provided for each country by the Central Intelligence Agency (CIA). The real numbers for Arabic speakers and Islamic adherence were converted into percentages, an approach also used by Fourie et al. (2020), and Ghalia et al. (2019). According to Dou et al. (2018) and Fourie et al. (2020), a country pair may be considered religiously similar if they have a common religion across the majority of population.

Sharing a common language and religion were used as dummy variables, with a value of 1 if both nations in the pair shared a common language and religion, and a value of 0 otherwise.

Table 4.1 provides a summary of the variables used in this study and the sources of collected data.

Table 4.1. Variable measurement, data definitions and sources

Independent variable	Label	Expected sign	Measurement and data source
Economic factors			
Word of mouth effect and repeat visit	$LNRT_{ijt-1}$	β>0	Repeat visit and word-of-mouth effect. The number of tourists who returned to their home country in the previous year. Source: The number of tourists from the MAS https://mas.gov.sa/
Origin country (i) income	IO_{it}	β>0	The tourist origin country's real GDP per capita is calculated at a constant USD 2,000. Source: World Bank, WDI.
Destination (j) country income	ID_{jt}	β>0	The tourist destination country's real GDP per capita is calculated at a constant USD 2,000. Source: World Bank, WDI.

Cost of living at the destination	p_{ijt}	β<0	Relative tourism price measured by CPI of Saudi Arabia divided by CPI of origin country adjusted by exchange rates. Source: The IMF and International Financial Statistics.
Cost of travel	$LnCT_{ijt}$	β<0	A proxy multiplying the geographic distance (measured in kilometres) with crude oil price. Crude oil price data source: Statistical Review of World Energy https://www.bp.com/en/global/corporate/energy-economics/statistical-review-of-world-energy.html Bilateral distance variable source : CEPII http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp
Tourism investment at the destination	$LnINVEST_{jt}$	β>0	Measured by capital investment in travel and tourism in terms of GDP (percentage) in (i) at time (t). Source: The WTTC
Destination country factors			
Political risks	$PRISK_{jt}$	β<0	Measured by averaging 12 variables reflecting political component: (1) Government stability (GS); (2) Military in politics (MP); (3) Socio-economic conditions (SC); (4) Religion in politics (RP); (5) Investment profile (IP); (6) Law & order (LO); (7) Internal conflict (IC); (8) Ethnic tensions (ET); (9) External conflict (EC); (10) Democratic accountability (DA); (11) Corruption (CC); (12) Bureaucracy quality (BQ). Source: ICRG, the PRS Group. https://epub.prsgroup.com/products/international-country-risk-guide-icrg
Human rights	HI_{jt}	β>0	Measured by the Cingranelli and Richards (CIRI) Human Rights Dataset, contains quantitative information based on standards on government compliance with 15 globally recognised human rights, including internationally recognised women and worker's rights (that concern Saudi Arabia) and other rights. Source: The CIRI Human Rights Data Project, http://www.humanrightsdata.com/
Relative temperature	TEM_{ijt}	β<0	Measured by ratio of origin country temperature to destination country temperature. Source: https://climateknowledgeportal.worldbank.org/download-data
Prosperity index	$LnPI_{jt}$	β>0	Prosperity index includes nation's social capital, education, governance, security, safety, personal freedom, and health. Source: The Legatum Prosperity Index- The Legatum Institute, https://www.prosperity.com/
Health risks	HR_t	β<0	Source: World Pandemic Uncertainty Index (WUPI) by Ahir et al., 2021.
Trade openness	TRADEij	B>0	Trade is the sum of exports and imports of services and goods measured as a share of GDP. Source: The World Bank, Direction of Trade Statistics, and the IMF.
FDI	FDIij	B>0	FDI is defined as nett outflows as a percentage of GDP. Source: The World Development Indicators of the World Bank.
The number of expatriate employees	$EXPWOR_{ij}$	B>0	Total expatriate workers by the origin country. Source: The United Nations' Immigration Database.
The number of overseas students	$lnOVESTU_{ji}$	B>0	The number of Saudi overseas students. Source: Data and Statistics Centre, Saudi Ministry of Education https://www.moe.gov.sa/en/knowledgecenter/dataandstats/Pages/infoandstats.aspx

Cultural affinity	$Language_{ij}$ $Religion_{ij}$	B>0	Sharing common: language and religion between (i) and (j) (dummy variable). Source: CEPII and Central Intelligence Agency(CIA). Dummy variable, 1 if the destintion and origin country shares common language and religion, otherwise 0.
Hajj incident	$DHAJ_i$	β<0	Dummy variable, 1 for 2015 and 2016, 0 otherwise.
Visa restrictions	DVRij	β<0	Dummy variable, 1 if there are restrictions on the Saudi visa in the country of origin of the tourist, 0 if not. https://www.saudiarabiavisa.com/entry-requirements/

4.6. Data analysis

In order to address the study objectives and hypotheses, a dynamic panel data regression analysis was conducted. Descriptive statistics were computed first. The data were tested for multicollinearity among the explanatory factors using a pairwise correlation matrix. Prior to performing the regression analysis, the data were first checked for stationarity. Regression analysis requires that data be stationary in order to be able to make meaningful inferences. For GMM estimator diagnostic tests for autocorrelation and instruments, over-identification was carried out using the Arellano-Bond test and Sargan statistic test, respectively. For the ARDL estimator, this study examined the cointegration using two panel Kao and Pedroni tests.

4.7. Summary and conclusion

This chapter has explained and justified the study's chosen methodology to achieve the research aim. Empirical evidence has illustrated the nature of tourism demand and its determinants. In addition, the chapter has explained which countries were chosen for analysis for the study period 2000 to 2019. Various statistical tests were employed in the study, and these are outlined in the following chapter These were used to determine the relationship between tourism demand and economic and non-economic factors.

CHAPTER 5: PANEL DATA ANALYSIS, ESTIMATION RESULTS AND DISCUSSION

5.1. Introduction

This chapter applies the methodologies discussed in the previous chapter to test the hypothesises developed in Chapter three. It does so by examining the impact of economic variables (income, prices, travel costs, capital investment in the tourism sector, FDI, and trade openness) and non-economic factors (political risks, human rights, global health risks, relative temperature, word-of-mouth, expatriate workers, Saudi international students, and destination prosperity) on aggregate and disaggregate (religious, business, VFR) tourism demand in Saudi Arabia from 2000 to 2019. To achieve this objective, this chapter includes descriptive statistics, correlation matrices, unit root tests, and dynamic and static regressions. Furthermore, several robustness checks have been used to enhance the validity of the main analysis and the reliability of the regression results. For the estimation, the researcher used EViews 11 econometric software.

This chapter is organised as follows: Section 5.2 outlines the modelling of religious tourism demand using panel data with a GMM approach. Section 5.3 presents the modelling of business tourism demand using a panel ARDL model estimation approach, and Section 5.4 presents the same for VFR tourism demand models. Aggregate tourism demand modelling, using a panel ARDL model estimation approach, is presented in Section 5.5, and Section 5.6 compares the impacts of the factors on total, religious, business, and VFR tourism demand. Section 5.7 presents the modelling of expatriate worker tourism demand with a panel ARDL model estimation approach, and Section 5.8 concludes the chapter.

5.2. Religious tourism demand

The religious tourism demand models specified in the model specification section of Chapter four were estimated in this chapter using GMM-DIFF estimates and panel data regression. This section discusses the empirical results obtained from modelling religious tourism demand. Firstly, descriptive statistics are described, then the correlation matrix and the unit root test, followed by the results of the religious demand model with GMM and FE models.

5.2.1. Descriptive statistics for religious tourism

The descriptive statistics of the data are presented in Table 5.1. Descriptive statistics contain the mean, median, minimum, maximum, and standard deviation used to measure the degree of convergence (Lin & Song, 2015).

Table 5.1. Descriptive statistics of international religious tourist arrivals from 2000 to 2019

	Number of tourists	Cost of travel	Cost of living at destination	Saudi income	Origin income	Capital investment	Relative temp.	Prosperity	Political risks	Global health risks	Human rights
Mean	346,460	254,005.60	2.45	20,523.43	10,892.90	24.99	1.11	56.476	66.96	3.32	7.67
Median	228,983	186,027.80	0.43	20,756.84	4,556.43	25.13	0.97	56.686	67.02	1.74	7.50
Maximum	1,925,085	1,249,174.00	13.78	21,399.10	47,900.44	26.93	3.23	57.999	70.21	11.18	12.00
Minimum	8,594	18,596.24	0.00	18,883.20	412.01	21.10	0.01	53.864	64.19	0.12	3.00
Standard deviation	348,707	223,985.20	3.89	760.72	12,864.94	1.62	0.49	1.227	1.98	3.73	2.72

Source: Author’s own calculations using EViews.

The results in Table 5.1 show that the total average number of tourists arriving in Saudi Arabia for religious purposes throughout the study period was approximately 346,460, ranging from 8,594 to 1,925,085. This demonstrates the significant variation in the number of tourists visiting Saudi Arabia for religious purposes from different nations, with a standard deviation of 348,706. The origin nations' income averaged USD 10,892.90, with a minimum of USD 412.01 and a maximum of USD 47,900.44. This significant degree of variability (the standard deviation of origin countries is 12,864.94) may be due to the fact that the data came from 21 countries with varying levels of development. The average income of the destination country (Saudi Arabia) was 20,523.43, ranging between 18,883.20 and 21,399.10. Saudi Arabia is one of the largest economies in the world and has been ranked 18th. Saudi Arabia is a petroleum-rich country, and its income is based on revenue from the oil industry. The volatility of oil prices has led to the volatility of GDP. Additionally, there was a high degree of variability in transport costs, which could be attributed to the fluctuation in oil prices and the length of distance between origin countries and Saudi Arabia. Relative price also shows a high level of variability. This could be because of the different exchange rates between the tourist origin country's currency and the Saudi riyal. The global health risks factor also shows great variability, which could be a result of using data from the WUPI to measure pandemics with differing impacts across origin countries. Across the study period (2000 to 2019), this included SARS (2002-2003), avian flu (2003-2009), swine flu (2009-2010), Ebola (2014-16), and coronavirus (from 2019). The average Saudi Arabian prosperity score was 56, with a maximum of 57.99, and a standard deviation of 1.22. The remaining variables did not show much variability.

5.2.2. Religious tourism demand correlation matrix

While the previous section reported the descriptive statistics of the variables used in the empirical investigation, this section presents the matrix showing the correlation between independent variables. To test the hypothesis that there is no correlation among the independent variables, the multicollinearity (approximate linear relationships between explanatory variables) test was employed. The Pearson correlation matrix evaluates the relationship between the variables in the sample. For this purpose, correlation coefficients between independent variables ≥ 70 percent should not cause bias in the regression estimates because of multicollinearity (Rousseau et al., 2018).

Table 5.2. Religious tourism demand: A Pearson correlation matrix between explanatory variables from 2000 to 2019

Variables	Cost of travel	Relative temp.	Prosperity	Origin income	Political risks	Global health risks	Capital investment	Human rights	Cost of living at destination	Saudi income
Cost of travel	1									
Relative temperature	0.188	1								
Prosperity	0.187	-0.002	1							
Origin income	-0.280	0.009	-0.039	1						
Political risk	0.241	0.036	0.611	-0.061	1					
Global health risk	-0.256	-0.041	0.0988	0.007	-0.228	1				
Capital investment in the tourism sector	--0.042	0.001	-0.537	0.034	-0.419	0.084	1			
Human rights	-0.185	-0.007	-0.619	0.052	-0.652	0.405	0.6412	1		
Cost of living at the destination	-0.117	-0.020	0.0588	0.438	0.075	-0.043	-0.048	-0.087	1	
Saudi income	0.158	-0.058	-0.502	-0.090	-0.150	-0.174	0.437	0.465	-0.145	1

Source: Author's own calculations using EViews.

Table 5.2 presents the Pearson correlation matrix estimation coefficients for the independent variables used in the religious tourism demand model. The empirical results reported in this table reveal that all estimating coefficients are less than Pearson's tolerance limit (0.7). The explanatory variables are not highly correlated. In this situation, since there is no correlation problem, the analysis can be continued using a set of factors in the estimations (Jamel, 2020).

5.2.3. Religious tourism demand unit root tests

In the previous section, multicollinearity among explanatory variables was tested by using a pairwise correlation matrix. This section presents the test results for stationarity of the variables that were used in these models before regression analysis was carried out. The test results for stationarity are presented in Tables 5.3 and 5.4, to ensure that the spurious correlation problem has been avoided. Estimating models with non-stationary variables typically leads to a problem of spurious regression.

Five methods of panel unit root test were applied to test the stationary of the variables, taking into consideration the asymptotic properties and the sample size of the tests. To test for unit roots (or stationarity), the null hypothesis is that all the panels contain a unit root. Tables 5.3 and 5.4 show the empirical results of the panel unit root test.

Table 5.3. Panel unit root tests for variables for religious purposes from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran & Shin (IPS) W-stat**		**ADF - Fisher Chi-Sq**		**PP - Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend		
Number of tourists	**-5.048 (0.000)**	**-3.083 (0.001)**	-	**-3.544 (0.000)**	**-2.555 (0.005)**	-1.421 (0.070)	**26.678 (0.011)**	**65.678 (0.011)**	**24.144 (0.000)**	**88.025 (0.000)**	Reject H_o	I(0)
Capital investment	**-9.834 (0.000)**	**-10.288 (0.000)**	-	**-2.443 (0.007)**	**-4.4033 (0.000)**	**-9.925 (0.000)**	**152.796 (0.001)**	**166.237 (0.000)**	**284.497 (0.000)**	**204.047 (0.000)**	Reject H_o	I (0)
Cost of living at destination	**-8.056 (0.0000)**	**-8.672 (0.000)**	-	**-3.052 (0.001)**	-2.2207 (0.986)	**-31.898 (0.000)**	**25.763 (0.000)**	**52.886 (0.000)**	**19.511 (0.0000)**	**19.986 (0.000)**	Reject H_o	I (0)
Cost of travel	2.456 (0.990)	**-1.688 (0.045)**	-	-0.2241 (0.588)	4.664 (0.275)	-0.538 (0.295)	6.429 (0.690)	33.774 (0.881)	7.781 (0.730)	35.586 (0.747)	Cannot reject H_o	I (1)
Saudi income	**-3.110 (0.000)**	**-3.435 (0.000)**	-	-0.246 (0.404)	-1.067 (0.149)	0.6960 (0.756)	4.419 (0.496)	23.593 (0.990)	4.655 (0.588)	23.559 (0.990)	Cannot reject H_o	I (1)
Origin income	-1.758 (0.348)	**-1.83209 (0.033)**	-	**-0.372 (0.008)**	-1.842 (0.967)	0.234 (0.592)	34.731 (0.779)	46.194 (0.302)	27.963 (0.952)	39.268 (0.596)	Cannot reject H_o	I (1)
Human rights	**-7.172 (0.000)**	**-4.251 (0.000)**	-	**-7.155 (0.000)**	**-5.075 (0.000)**	**-6.328 (0.000)**	**38.589 (0.000)**	**0.243 (0.000)**	**28.299 (0.000)**	24.350 (0.329)	Reject H_o	I(0)
Political risks	**-3.170 (0.000)**	**-4.851 (0.000)**	-	**-0.558 (0.000)**	**-2.732 (0.000)**	**-4.410 (0.000)**	**55.186 (0.000)**	**78.235 (0.000)**	35.632 (0.745)	**59.699 (0.037)**	Reject H_o	I (0)
Relative temp.	**-13.484 (0.000)**	**-10.624 (0.000)**	-	**-6.040 (0.000)**	**-15.946 (0.000)**	**-21.279 (0.000)**	**10.812 (0.000)**	**30.029 (0.000)**	**10.016 (0.000)**	**12.211 (0.000)**	Reject H_o	I (0)
Prosperity	**-8.489 (0.000)**	**-12.679 (0.000)**	-	**-5.779 (0.000)**	**-4.209 (0.000)**	**-4.252 (0.000)**	**66.743 (0.000)**	**87.320 (0.0001)**	**65.363 (0.000)**	**107.395 (0.000)**	Reject H_o	I (0)
Global health risks	**-3.152 (0.000)**	**-8.268 (0.000)**	-	**-6.716 (0.000)**	**-2.834 (0.002)**	**-3.221 (0.000)**	**34.909 (0.037)**	**64.199 (0.015)**	**49.703 (0.037)**	**57.9633 (0.051)**	Reject H_o	I (0)

Notes: All unit root tests were performed with the individual intercept, and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. Note that in the case of individual intercept (in EViews) we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary.

Table 5.3 presents the results of the unit root test from various methods. The null hypothesis is the presence of unit root and cannot be rejected in variables Saudi income, income of the origin country, and transport costs. This means these variables are not stationary on the level I(1). The null hypothesis can reject H_0 in the number of religious tourist arrivals to Saudi Arabia, political risks, destination prosperity, cost of living at the destination, human rights, capital investment in the tourism sector, and relative temperature. This means these variables are stationary at I(0). The results indicate that the variables of this model have different integrated orders I(0) and I(1).

Table 5.4. Panel unit root tests for variables on first difference (2000-2019) for all country models

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran & Shin (IPS) W-stat**		**PP - Fisher Chi-Sq**		**ADF – Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual intercept &Trend	-	individual intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend		
Number of tourists	**-21.487 (0.000)**	**-20.920 (0.000)**	**-**	**-16.345 (0.000)**	**-17.524 (0.000)**	**-19.012 (0.000)**	**262.905 (0.000)**	**189.468 (0.000)**	**337.630 (0.000)**	**308.244 (0.000)**	Reject H_o	I (0)
Cost of travel	**-12.248 (0.000)**	**-13.015 (0.000)**	**-**	**-7.492 (0.000)**	**-6.906 (0.000**	**-9.564 (0.000)**	**130.786 (0.000)**	**153.767 (0.000)**	**151.653 (0.000)**	**151.691 (0.000)**	Reject H_o	I (0)
Saudi income	**-15.074 (0.000)**	**-15.400 (0.000)**	**-**	**-9.348 (0.000)**	**-10.651 (0.000)**	**-9.564 (0.000)**	**185.962 (0.000)**	**152.239 (0.000)**	**120.446 (0.000)**	**180.067 (0.000)**	Reject H_o	I (0)
Capital investment	-2.302 (0.983)	**-7.633 (0.000)**	**-**	**-3.517 (0.000)**	**-4.429 (0.000)**	**-11.845 (0.000)**	**75.034 (0.001)**	**191.089 (0.000)**	**138.985 (0.000)**	**398.580 (0.000)**	Reject H_o	I (0)
Cost of living at destination	**-8.861 (0.000)**	**-16.840 (0.000)**	**-**	**-3.877 (0.000)**	**-8.313 (0.000)**	**-31.11 (0.000)**	**138.711 (0.000)**	**249.698 (0.000)**	**172.745 (0.000)**	**371.288 (0.000)**	Reject H_o	I (0)
Origin income	**-11.307 (0.000)**	**-7.382 (0.000)**	**-**	**-3.961 (0.000)**	**-8.365 (0.000)**	**-6.753 (0.000)**	**148.106 (0.000)**	**135.167 (0.000)**	**179.09 (0.000)**	**178.711 (0.000)**	Reject H_o	I (0)
Human rights	**-16.511 (0.000)**	**-14.140 (0.000)**	**-**	**-20.194 (0.000)**	**-17.094 (0.000)**	**-14.639 (0.000)**	**147.092 (0.000)**	**170.934 (0.000)**	**253.310 (0.000)**	**202.627 (0.000)**	Reject H_o	I(0)
Political risks	**-1.831 (0.033)**	**-16.209 (0.000)**	**-**	**-0.744 (0.000)**	**-7.228 (0.000)**	**-11.078 (0.000)**	**100.722 (0.000)**	**174.993 (0.000)**	**111.450 (0.000)**	**174.752 (0.000)**	Reject H_o	I (0)
Relative temp.	**-17.849 (0.000)**	**-7.893 (0.000)**	**-**	**-6.657 (0.000)**	**-22.117 (0.000)**	**-13.530 (0.000)**	**325.954 (0.000)**	**229.178 (0.000)**	**314.678 (0.000)**	**395.228 (0.000)**	Reject H_o	I (0)
Prosperity	**-15.039 (0.000)**	**-12.439 (0.000)**	**-**	**-3.855 (0.000)**	**-7.601 (0.000)**	**-2.604 (0.004)**	**143.348 (0.000)**	**88.757 (0.000)**	**270.329 (0.000)**	**218.787 (0.000)**	Reject H_o	I (0)
Global health risks	**-14.568 (0.000)**	**-16.160 (0.000)**	**-**	**-15.747] (0.000)**	**-8.459 (0.000)**	**-12.093 (0.000)**	**135.811 (0.000)**	**190.600 (0.000)**	**134.640 (0.000)**	**237.769 (0.0000)**	Reject H_o	I (0)

Notes: All unit root tests were performed with the individual intercept, and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values in squared parentheses. In the case of individual intercept (in EViews) we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary.

The panel unit root tests were conducted on the first differences of the variables, as shown in Table 5.4. The null hypothesis of a unit root was rejected in all variables on the first difference. Therefore, some variables used in the model become stationary on the first differences. Overall, as illustrated in Tables 5.3 and 5.4, panel unit root tests were performed on the levels and the first differences of all the variables to check the level of integration of the model's variables. The test results show that some variables are not stationary on level I(0) and integrated I(1), thus the variables used in the model are a mixture of I(1) and I(0).

5.2.4. Empirical results and discussion on religious tourism models

This section presents the results of the GMM estimator for religious tourism in Saudi Arabia and the tests of model validity. A panel regression model estimator was also considered to ensure the results were robust.

5.2.4.1. Estimate GMM models.

The panel data contained cross-sectional data covering 21 origin countries, and economic and non-economic factors that influenced religious inbound tourism demand in Saudi Arabia for the period 2000 to 2019. The GMM panel regression model given in Equation 3 in Chapter four consists of a lagged dependent variable to measure the word-of-mouth effect and repeat visits.

This study contained a large number of independent variables and a small number of panel data, plus a large number of independent variables and a small number of observations in the time dimension. Roodman (2009b) maintained that too many instruments compared to the size of the cross-sectional sample size can lead to weakened specification tests and biased coefficient and standard error estimates. Therefore, this study estimated the panel regression model in four specifications[5], as considered in previous studies (Barman & Nath, 2019; Lorde et al., 2016; Viljoen et al., 2019). The variables were mostly consistent in effect and significance, with different specifications.

[5] The first specification, Model 1, shown in column 1 of Table 5.5, includes economic factors that are one-year lagged tourist arrivals, per capita GDP of both the origin and destination countries, cost of travel, cost of living at the destination, and investment in the tourism sector. The second specification, Model 2, shown in column 2, includes one-year lagged tourist arrivals, per capita GDP of both the origin and destination countries, cost of travel, human rights, and political risks; the third specification, Model 3, shown in column 3, includes one-year lagged tourist arrivals, per capita GDP of both the origin and destination countries, cost of travel, cost of living at the destination, global health risks, and temperature. The fourth specification, Model 4, shown in column 4, includes one-year lagged tourist arrivals, per capita GDP of origin country, cost of travel, and the prosperity index of the destination (the GDP of the destination country is excluded from this model since it includes the prosperity index of destination).

Table 5.5. Results from the GMM from 2000 to 2019

Independent variables	Model 1 economic coefficient prob	Model 2 coefficient prob	Model 3 coefficient prob	Model 4 prosperity index coefficient prob
Word of mouth & repeat visit RTijt-1	0.486 *** (0.000)	0.450*** (0.000)	0.436*** (0.000)	0.438*** (0.000)
Economic factors				
Saudi income IDj	2.019*** (0.0000)	1.634*** (0.0003)	0.800*** (0.0000)	1.349*** (0.007)
Origin income IOi	0.266*** (0.000)	0.475 (0.317)	0.113** (0.024)	0.622* (0.099)
Cost of travel CT_{ij}	-0.222*** (0.000)	-0.215* (0.081)	-0.261*** (0.000)	-0.370*** (0.0309)
Cost of living at destination P_{ij}	-0.544*** (0.000)	-	-	-
Capital investment $INVEST_j$	0.028*** (0.000)	-	-	-
Non-economic factors				
Relative temp. TEMj	-	-	-0.263*** (0.007)	-
Human rights index HIj	-	0.231** (0.052)	-	--
Political risks PRISKj	-	-0.879*** (0.004)	-	-
Prosperity index DPj	-	-	-	0.021** (0.073)
Global health risks HR	-	-	-0.001 (0.811)	-
Visa restrictions DVR_{IJ}	-	-0.515*** (0.0001)	-	
Wald test	440 (0.000)	125 (0.000)	386 (0.00)	279 (0.0000)
Sargan test	18.264 (0.249)	15.650 (0.405)	14.406 (0.494)	15.898 (0.950)
Arellano–Bond test AR(1)	0.997	0.998	0.729	0.798
Arellano–Bond test AR(2)	0.999	0.999	0.880	0.746

Source: Author's estimation
Note: *** 1% significant, **5% significant and * 10% significant

The results in Table 5.5 show that the estimated coefficients for both sign and magnitude are almost aligning with the expected sign. The following tests were carried out in this study: the Wald test provides support to the joint significance of the explanatory variables; the Sargan–Hansen test developed by Arellano and Bond (1991) was applied for over-identification restrictions (the Sargan test did not indicate a serious problem with the validity of these instrumental variables); and AR (1) and AR (2) first-order and second-order serial correlation tests confirmed the models performed satisfactorily.

Economic factors

The results shown in Table 5.5 indicate that the word-of-mouth effect (habit persistence) and repeat visits are important factors in explaining religious tourism demand in Saudi Arabia. For all four specification models, the estimated coefficient of the lagged tourist arrivals was positive and statistically significant. This result suggests that pilgrims who visited Saudi Arabia in the previous year became an important source for promotion, information and spreading of their experiences in their home countries. Moreover, from 0.43 to 0.48 percent of the total inbound religious tourism arrivals to Saudi Arabia can be explained by repeat visits and word-of-mouth effects. This finding is supported by a related argument: according to Islamic jurisprudence, Muslims can perform additional Hajj and Umrah (Nafl, which refers to an action that is voluntary or optional) as many times as they wish. When travel to the Umrah and the Hajj become easier and the quality of service is high, people are willing to make repeat visits (Raj & Bozonelos, 2015).

A review of the literature illustrated that word-of-mouth has not yet been examined in terms of religious tourism demand, but the evidence available does indicate that word-of-mouth has a significant impact on international tourism demand (Buigut et al., 2015; Fourie & Santana-Gallego, 2013; Garín-Mun, 2006; Garin-Munoz & Montero-Martín, 2007; Ghaderi et al., 2017; Habibi, 2017; Khadaroo & Seetanah, 2008; Mendieta-Aragón & Garín-Muñoz, 2020).

Regarding the impact of gravity factors on the number of international religious tourists to Saudi Arabia, the results presented in Table 5.5 indicate that in the signs on income of both origin and destination countries, coefficients are as expected, positive and statistically significant at the 1 percent level for all estimate models. Based on the gravity theory perspective, this suggests that religious international tourists flow to Saudi Arabia increases when the economic size of the two countries increases. The economic size of the origin country is therefore extremely significant to the rise in tourist arrivals in Saudi Arabia. When the tourist's origin country income increased by 1 percent, Saudi Arabia's religious tourism demand increased by rang from 0.11 to 0.62 percent ceteris paribus, as evident in the demand model results. That suggests that Saudi Arabia is one of the origin countries' preferred tourism destinations if their income increases. As Muslims believe that they must undertake the pilgrimage to Mecca at least once in their lifetime, they do so when the opportunity arises. However, most people do not undertake it until late in life, when they have sufficient funds to make the trip. However, the trip to

Mecca is not exclusively a religious pilgrimage. After the Hajj rituals are complete, the majority of pilgrims engage in trade and shopping to buy gifts for friends and family back home (Aziz, 2001; Muneeza et al., 2018).

This result is consistent with Shaheen (2019), who found a positive impact of origin country income on religious tourism. Prior research on religious tourism (e.g., Crain, 1996; Norman, 2004; Rinschede, 1992) primarily considered religious travel to be a spiritual phenomenon and did not find a link between the income of the origin country and the decision to participate in religious tourism. In this study, however, Saudi Arabia's income (per capita GDP) impact is higher than the tourist origin country's per capita GDP. The estimated coefficient suggests that when Saudi's income levels increased by 1 percent, the number of religious tourist arrivals increased into Saudi Arabia by 2.01,1.63,0.80 and 1.34 percent respectively. This empirical evidence implies that there is a positive relationship between religious tourism demand and the development level of the destination.

As shown in the first column of Table 5.5, capital investment in the tourism sector in Saudi Arabia had a positive impact on religious tourism demand. A 1 percent increase in tourism investment increased religious tourism demand by 0.028 percent, other factors being held constant. Capital investment in Saudi Arabia's travel and tourism sectors can lead to building hotels, restaurants, or catering services for tourists, making transportation services affordable and reliable, and improving tour guide operations. According to Choe and O'Regan (2015), although substantial infrastructure investment has made Thailand, Singapore, and Malaysia popular tourist destinations, other countries, including Myanmar and Laos, have struggled to attract visitors due to inadequate infrastructure.

One additional finding of this study is that the cost of living at the destination (relative price) and cost of travel variables had significantly negative effects on religious tourism, indicating that international religious tourists prefer nearby destinations with relatively lower living costs. The estimated religious tourism demand price elasticity was 0.54, which indicates that religious tourists were price sensitive, meaning that if tourism prices in Saudi Arabia increased by 1 percent, religious tourist arrivals reduced by 0.54 percent, ceteris paribus. In contrast, Shaheen (2019) found a positive relationship between the price of tourism in Saudi Arabia and demand for religious tourism in all countries in the sample. She claimed that religious tourism is 'Veblen good' (a type of luxury product that increases in demand as its price rises), implying that it is linked to the economic status of the people in the nation of origin. These pricey products and services reflect the consumer's high social status.

The effect of cost of travel was negative and statistically significant on religious tourism in all the models tested, as shown in Table 5.5. This indicates that the lower the cost of travel to Saudi Arabia from the country of origin, the greater increase in demand for religious tourism. Thus, tourist arrivals in Saudi Arabia are sensitive to the cost of travel. A 1 percent increase in the cost of travel between the origin country and Saudi Arabia decreased religious tourism demand 0.22,0.21,0.26 to 37 (on average of four models by 0.23) percent when other factors are held constant. This result is consistent with the findings of Shaheen (2019), which indicated that travel costs had a negative and statistically significant impact on religious tourism in low-income countries. However, this finding is inconsistent with the same study when applied to higher-income countries such as Kuwait, Qatar, and the United Arab Emirates, where travel costs have a positive impact on religious tourism. This discrepancy can be attributed to the fact that these countries have oil revenue-based economies (and Shaheen measured travel costs by crude oil price), and any increase in the international oil price could lead to a rise in demand for religious tourism.

Non-economic factors

As expected, the regression results shown in Table 5.5 indicate that the impact of political risks was negative and had a significant impact on religious tourism demand. This means that a high level of political risk leads to low visitation. Political risk was considered by examining whether political issues in the Middle Eastern region have an impact on religious tourism demand in Saudi Arabia. The OECD 2016 States of Fragility report classified Saudi Arabia as having “moderate political stability”. Regional instability has been seen as one of the barriers to the operation of Saudi Arabian tourism, along with the harsh climate and visa restrictions (Sadi & Henderson, 2005).

Visa restrictions were negatively associated with the number of religious tourist arrivals. This suggests that visa requirements represent a critical limitation and deterrent to religious tourist flows. Although the literature did indicate that a strict visa regime is one significant inhibitor faced to expanding Saudi Arabia’s tourism industry (Ekiz et al., 2017), there is no empirical evidence of the impact of visa restrictions specifically on the number of religious tourist arrivals.

This study found that the estimated coefficient of the prosperity index had a positive and significant impact on religious tourism demand in Saudi Arabia, implying that improvement in prosperity in Saudi Arabia would increase religious tourism demand. These findings indicate that the number of international tourists tends to increase when the destination prosperity improves. This result extends the findings of Gholipour et al. (2022), that international tourists' spending is higher in a destination where local residents are happier.

It is always a top priority for the Saudi Arabian government to ensure that pilgrims' health, safety, and well-being are protected. The Hajj pilgrimage is one of the largest annual mass gatherings of people in the world, therefore, the country needs proper healthcare systems to handle health challenges during each Hajj season. Pilgrims face numerous health risks, including hazards and infectious diseases (Ahmed et al., 2006; Al-Tawfiq et al., 2017). Islamic Sharia goals demand the safeguarding of human souls while providing all of the essential amenities to enable pilgrims to complete the rituals of Hajj or

Umrah and to reach the holy locations smoothly and easily. With the increase of pilgrims performing Hajj and Umrah, the country's prosperity will continue to be a priority.

Enhancing and updating the quality of health care and the environment, as well providing translation services and highly skilled human resources, transportation infrastructure, and technology, is critical to ensure pilgrims have a safe and enjoyable experience. This factor has not been examined in previous research in terms of the impact on the number of religious tourist arrivals. To the best of our knowledge, very few studies exist that investigate the impact of destination prosperity on tourist movements across countries. The only study that considered the prosperity factor in the tourism demand context is Sokhanvar et al. (2018), which found a significant link between tourism expenditure and the prosperity of origin countries. As such, this current study contributes new insights to the body of knowledge.

As shown in Table 5.5, the estimated coefficients of global health risks had a negative but not significant impact on religious tourism demand. In other words, global health risks did not significantly impact the number of religious tourist arrivals to Saudi Arabia. Evidence of the negative impact of global health risks and infectious disease on religious tourist flow is consistent with the results reported in several other studies (Mróz, 2021; Nasir et al., 2020; Prasetio et al., 2022).

The results of the current study indicate that the respect of the government for human rights in the destination country positively impacts religious tourism demand. A high score represents a high level of respect for all aspects of human rights aspect. A positive relationship between the human rights factor and the number of tourists was expected. Saudi Arabia should maintain its image as a safe and secure destination. This is important for meeting the goals of Vision 2030 and to increase pilgrimage numbers. As noted previously, in 2018, the Saudi Arabian government took initiatives to enhance human rights by giving women the right to drive and allowing women over 21 years of age to travel freely and obtain passports without permission from a male guardian (Elyas & Aljabri, 2020).

Relative temperature between Saudi Arabia and the origin country has a negative and significant impact on religious tourism demand. A one percent increase in temperature in Saudi Arabia during the Hajj season decreased religious tourism demand by 0.26 percent, other things being held constant. The Hajj incident effect was not statistically significant and was therefore not included in the model estimation. The results of the estimation of the panel GMM model indicate that public policies seeking to improve the destination country's prosperity, infrastructure, and security (while minimizing political risks) can accelerate international religious tourist inflows to Saudi Arabia.

It should be highlighted that the coefficients estimated in GMM, as shown in Table 5.5, were for short-run demand elasticities. However, pilgrims require time to plan their trips to visit holy cities. During their travel planning, if there is a change (increase or decrease) in one of the determinant factors (such as the cost of travel), the short-term reaction is lower but the reaction to this change is higher in the long run. In addition, the destination country needs long-run elasticities for tourism planning and policy formulation to maintain competitiveness. Thus, for policy analysis purposes, a sensitivity analysis was conducted to examine how religious tourism demand responded to a one percent increase or decrease due to the fluctuation of economic and non-economic factors in the long run. This indicated that estimated tourism demand elasticities are often lower in the short run than in the long run. This study obtained long-run elasticities by undertaking some transformations. Table 5.6 shows the long-run elasticities of determinants that were calculated by dividing each short-run elasticity coefficient by the coefficient of lag independent variable β_1 -1 in each model specification (Garín-Muñoz & Montero-Martín, 2007).

Table 5.6. Estimated long-run elasticity of the factors from 2000 to 2019 in GMM models

Dependent variable	Model 1	Model 2	Model 3	Model 4
Word of mouth & repeat visit RT_{ijt-1}	0.946	0.819	0.773	0.779
Saudi income IO_{jt}	3.929	2.973	1.419	1.349
Origin income ID_{it}	0.517	0.865	0.199	1.106
Cost of travel CT_{ijt}	-0.432	-0.391	-0.463	-0.658
Cost of living at destination p_{it}	-1.058	-	-	-
Capital investment $LNINVEST_{it}$	0.055	-	-	-
Human rights index HI_{it}	-	0.419	-	-
Political risks $PRISK_{it}$		-1.599	-	-
Visa restrictions DVR_{IJ}	-	-0.936	-	-
Prosperity index pI_{it}	-	-	-	-
Global health risks HR	-	-	-0.017	-
Relative temp. TEMj	-	-	-0.466	-

Source: Author's estimation.

As can be seen in Table 5.6, the long run, repeat visits and the word-of-mouth effect contributed to 84% of pilgrim visits to Saudi Arabia, where the stable economy and economic prosperity have a significant impact on religious tourism demand. A 1 percent increase in Saudi Arabia's income increased religious tourism demand in the long-run by 3.92,2.97,1.41 and 1.34 percent respectively (on average 2.41) and the origin country income increased religious tourism demand in the long-run by 0.51,0.86,0.19 and 1.10 percent respectively (on average 0.67). Religious tourism demand in Saudi Arabia is very sensitive to the cost of living at the destination; therefore, any changes in the destination price level would have a substantial impact in the long run compared to the cost of travel and the estimated long-run elasticities, which was -1.05 percent the cost of travel were -0.43,-0.39,-0.46 and -0.65 percent respectively (on average -0.48) . Capital investment in the tourism sector by the Saudi Arabian government to diversify the economy away from reliance on energy would increase religious tourism demand by 0.05 percent in the long run. Saudi Arabia's human rights and prosperity would increase religious tourism demand by 0.41 and 0.03 respectively, and political risk and visa restrictions would decrease demand by -1.59 and -0.93 respectively.

5.2.4.2 Panel regression model estimates

The previous section employed the GMM-DIFF method to examine the major determinants of international tourist arrivals to Saudi Arabia. However, there is doubt about the reliability of unit root tests and cointegration tests in small sample sizes (in this thesis, T=20) (Baltagi, 2021). Therefore, this study also considered all variables to be stationary and then estimated tourism demand by using panel regression models. Panel data has three approaches for its estimation: POLS, FE and RE. Guided tests and statistics aid the choice of the most appropriate model between them. Most studies of international tourism demand have used panel regression models, assuming that there is a long-term relationship between tourism demand and its causes without looking into the stationarity of variables.

Model specification test

The initial stage of the selection model process was to carry out the Chow test. The null hypothesis of the Chow test is that POLS is more appropriate than FE, the alternative hypothesis is that the FE is more appropriate than POLS. As shown in Table 5.7, the results of the Chow test imply that the FE is more appropriate to estimate all regression models and that the probability value is less than (0.05). Thus, the null hypothesis was rejected. This means that the FE was considered more appropriate to estimate this regression model.

To choose between POLS or RE, the Breusch-Pagan LM test was applied. The null hypothesis of the Breusch–Pagan LM statistic tests is that the POLS is more appropriate than the RE. The estimator is appropriate, against the random effects of alternatives. Table 5.7 shows the outcomes the Breusch-Pagan LM tests. The null hypothesis was rejected, and RE was considered more appropriate to estimate this regression model. The Hausman test was applied in order to decide between FE and RE panel-data models. The probability value for the Hausman test statistics was less than 0.05 (p-value < 0.05). This means the null hypothesis was rejected, and the FE effects model was considered more appropriate for this model.

Table 5.7. Specification tests for religious panel regression method to choose the most appropriate model between POLS, FE and RE

Specification tests	Statistic (Prob.)	Choose between	Decision (Selection)
Chow test	24.374 (0.000)	POLS /FE Null hypothesis: POLS is more appropriate to estimate panel than FE.	FE Reject the null hypothesis.
Lagrange multiplier tests (Breusch-Pagan-LM test)	114.897 (0.000)	POLS /RE Null hypothesis: POLS is more appropriate to estimate panel than RE.	RE Reject the null hypothesis.
Hausman test	17.499 (0.031)	FE/RE The preferred model is RE.	FE Reject the null hypothesis.
Preliminary tests			
Slope homogeneity test	$\hat{\Delta}$ = 15.734 (0.151) $\hat{\Delta}_{adj}$ = 10.928 (0.449)	Null hypothesis: slope coefficients are homogenous.	Cannot reject the null hypothesis of slope homogeneity. Thus, slope coefficients were homogenous in cointegration equations.
Cross-section dependence: Breusch-Pagan LM	0.2783 (0.780)	Null hypothesis: there is no cross-section dependence.	Cannot reject the null hypothesis. Thus, there is no cross-sectional dependence in panel data analysis.
Pesaran scaled LM	0.466 (0.532)		
Bias-corrected scaled LM	0.4666 (0.699)		
Pesaran CD	0.163 (0.994)		
Normal distribution Jarque-Bera (JB) probability	1.709 (0.424)	Null hypothesis: residuals are normally distributed.	Cannot reject the null hypothesis. Thus, residuals are normally distributed.

Source: Author's own calculations using EViews.
Note: Simple pooled ordinary least squares (POLS), fixed effect model (FE) and random effect model (RE) $\hat{\Delta}$ *and* $\hat{\Delta}_{adj}$ tests are a modified version of the Swamy (1970) test proposed by Pesaran and Yamagata (2008). In both cases, slope homogeneity is the null hypothesis.

In order to determine whether the slope coefficients were homogenous or not, the null hypothesis of the test was: slope coefficients are homogenous. Table 5.7 presents the results of a slope homogeneity test. In light of the results, the null hypothesis could not be rejected, and it was determined that slope coefficients were homogeneous. It was concluded in this case that heterogeneity did not exist across samples.

The existence of cross-sectional dependence implies that a shock affecting one of the countries can be transmitted to the others. The null hypothesis is that there is no cross-sectional dependence, implying that there is no association between the disturbances at different cross-sections (countries). The results of cross-section dependence indicated that the test's p-value > 0.05. This indicates that the null hypothesis of no cross-sectional dependence cannot be rejected, and there is no cross-sectional dependence across the countries analyzed at the 1 percent level. This means that there is no certain level of dependence among countries.

The Jarque-Bera (JB) test is utilized to assess the normality of the residuals. Given that its value is more than 5 percent, the residual is normally distributed. The Pesaran CD test was applied to check the absence of cross-section dependence. Since its value was greater than 5 percent, the absence of cross-section dependence was confirmed.

The estimated FE model results are presented in Appendix B. These show the result of international tourism determinants to Saudi Arabia from 21 countries of origin. The FE panel goodness of fit test using R^2 was high on the FE model, indicating 74 percent. This suggests that the estimated predictors explain 74 percent of the variation in international tourism arrivals to Saudi Arabia. The p-value of all models (Prob >F=0.000) is statistically significant, which means that the estimated predictors reliably predict international tourism arrivals to Saudi Arabia for religious purposes. The results show that the model performs satisfactorily. The magnitudes and signs of the coefficients are theoretically reasonable and significant. The estimated results of the FE model are consistent with the dynamic estimation results in signs.

Most gravity models introduce cultural affinity factors such as sharing a common religion and language between origin and destination countries. These are the most frequent and significant proxies for social-preferential relationships (Vietze, 2012). They are estimated in the RE model as the FE model does not permit the estimate of time-invariant variables, such as religion or language dummies. Sharing a common religion positively impacts religious tourism demand. Religious affiliations have some effect on international tourists when the origin countries and Saudi Arabia share a common religion, which means they have the same values, understand the same taboos, and there is less conflict between tourists and residents (Wang & Xi, 2016). By contrast, this result suggests that sharing a common language between the origin and destination countries tends to dilute the tourism flows. This may be because a common language is less important to the flow of religious tourists to Saudi Arabia. Authorities in the destination country have trained staff who know many languages and are able to deal with Muslims who come from different parts of the world.

5.3. Business tourism demand

In the previous section, religious tourism was estimated using GMM dynamic models since the cross-sectional dimension was relatively large (N= 21) and the time dimension small (T=20). Business, VFR, aggregated, and expatriate worker tourism demand models, however, were estimated using ARDL models because their cross-sectional dimension was smaller than the time dimension.

This section discusses the descriptive statistics, the correlation matrix, and unit root tests, as well as the results of the business demand model using the ARDL model and FE.

5.3.1. Descriptive statistics for business tourism demand

The data needed to be thoroughly evaluated before estimating. The essential features of the data in the study were described using descriptive statistics. The descriptive statistics of dependent and independent variables are shown in Table 5.8. This summarises the descriptive statistics, including mean, median, minimum, maximum and standard deviation for all of the variables used in the empirical analysis of business tourism demand for the years 2000 to 2019. The dependent variable was the number of business tourist arrivals to Saudi Arabia.

Table 5.8. Descriptive statistics of international business tourist arrivals from 2000 to 2019

	Number of business tourists	Cost of travel	Origin income	FDI	Trade openness	Cost of living at destination	Relative temp.
Mean	126,239.10	340,200.80	14,575.40	2.68	2.639	2.44	0.94
Median	74,029.50	200,356.90	3,497.81	1.24	1.215	0.28	0.97
Maximum	910,587.00	1,249,174.00	55,809.01	8.5	8.496	13.78	1.32
Minimum	2,075.00	23,415.12	720.36	0.21	0.206	0.00	0.44
Standard deviation	158,447.10	313,804.70	18,839.81	2.78	2.772	3.87	0.21

Source: Author's own calculations using EViews.

Earlier in this chapter, data on Saudi income, destination prosperity, political risks, global health risks, human rights and capital investment in the tourism sector were described in the descriptive statistics table for religious tourism (see Table 5.1). The same data were used for all models regardless of the purpose of the visit, as these variables focus on the destination country. Consequently, there is no need to report them again.

The data presented in Table 5.8 shows that the overall average number of international business tourist arrivals to Saudi Arabia for all countries in the model (11 origin countries) over the period from 2000 to 2019 was 126,239.10, with a minimum of 2,075 and a maximum of 910,587. This indicates that the number of tourists visiting Saudi Arabia from the origin countries was highly varied (with a standard deviation of 158,447.10). The average income of the origin countries was 14,575.40, with a minimum of 720.36 and a maximum of 55,809.01. This variability is high (with a standard deviation of 18,839.81) and may be because the data came from nations with different levels of development (developing and developed countries). Furthermore, there was high variability in relative price, which could be because of the different exchange rates between the tourist origin country's currency and the Saudi riyal. The remaining factors, relative temperature, travel cost, FDI, and trade openness, exhibited little variation.

5.3.2. Business tourism demand correlation matrix

While the previous section reported the descriptive statistics of the variables used in the empirical investigation, this section presents the correlation matrix showing the correlation between independent variables. Table 5.9 provides a summary of the estimated coefficients of the Pearson correlation matrix between all indicators included in this model. The empirical results in this table show that the coefficients of all estimations were inferior to the Pearson tolerance limit of 0.7, indicating that there were no multicollinearity problems while estimating the equation. Since there is no correlation issue, the investigation and estimation could continue in this instance.

Table 5.9. Business pairwise correlation matrix: A Pearson correlation matrix between explanatory variables from 2000 to 2019

Correlation	Cost of travel	Trade openness	Political risks	Prosperity	Human rights	Saudi income	Origin income	Global health risks	Cost of living at destination	Capital investment	FDI	Relative temp.
Cost of travel	1											
Trade openness	0.478	1										
Political risks	0.179	0.095	1									
Prosperity	0.013	0.0039	0.541	1								
Human rights	-0.183	-0.081	-0.419	-0.025	1							
Saudi income	0.218	0.120	-0.434	-0.496	0.085	1						
Origin income	0.004	0.182	-0.040	-0.034	0.014	0.140	1					
Global health risks	-0.254	-0.130	-0.465	0.096	0.196	-0.133	0.005	1				
Cost of living at destination	-0.506	-0.116	0.099	0.078	-0.087	0.022	0.534	-0.049	1			
Capital investment	0.008	-0.022	-0.389	-0.734	0.019	0.434	0.032	0.090	-0.063	1		
FDI	0.114	0.076	0.684	0.691	-0.510	-0.477	-0.042	-0.211	0.110	-0.522	1	
Relative temp.	0.374	0.241	0.022	0.006	-0.001	0.184	0.222	-0.009	-0.146	-0.007	0.002	1

Source: Author's own calculations using EViews.

5.3.3. Business tourism demand unit root tests

The previous section discussed the multicollinearity among explanatory variables, which was tested by using a pairwise correlation matrix. This section presents the test results for stationarity of the variables that were used in these models before regression analysis was carried out. This study conducted the panel unit root test for both dependent and independent variables. It is worth noting that the panel unit root tests were conducted on levels and first differences of the variables, Saudi income, destination prosperity, political risks, global health risks, human rights and capital investment in the tourism sector in the first section (as shown in Tables 5.10 and 5.11). The same data were used for all models regardless of the purpose of visit, as the variables relate to the destination country. The null hypothesis being tested was that the data contain a unit root.

Table 5.10. Panel unit root tests for variables on level for business purposes from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		Breitung t-stat		Im, Pesaran & Shin (IPS) W-stat		ADF - Fisher Chi-Sq		PP - Fisher Chi-Sq		Decision	Order of integration
Variables	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend		
Number of tourists	**-6.445 (0.000)**	**-4.255 (0.000)**	**-**	-0.513 (0.303)	**-3.690 (0.000)**	**-1.750 (0.040)**	**65.919 (0.000)**	32.605 (0.067)	**71.436 (0.000)**	**33.492 (0.055)**	Reject H_o	I(0)
Origin income	-1.501 (0.903)	-1.427 (0.988)	**-**	**-2.754 (0.000)**	-0.686 (0.753)	-1.856 (0.968)	29.799 (0.475)	28.475 (0.160)	28.712 (0.535)	**34.698 (0.025)**	Cannot reject H_o	I(1)
Cost of travel	-1.277 (0.101)	-1.962 (0.975)	-	-0.243 (0.403)	-0.385 (0.350)	-3.403 (0.999)	3.143 (0.990)	17.589 (0.730)	24.029 (0.770)	18.621 (0.668)	Cannot reject H_o	I(1)
FDI	**-4.021 (0.000)**	-0.976 (0.164)	**-**	**-3.992 (0.000)**	**-2.604 (0.000)**	-0.971 (0.834)	**39.725 (0.017)**	10.642 (0.979)	**84.601 (0.000)**	5.174 (0.999)	Reject H_o	I(0)
Trade openness	-1.524 (0.063)	-1.132 (0.128)	**-**	-0.077 (0.469)	-1.286 (0.099)	-1.246 (0.893)	9.710 (0.987)	10.506 (0.981)	15.622 (0.834)	9.576 (0.988)	Cannot reject H_o	I(1)
Cost of Living at Destination	-3.705 (0.999)	-4.809 (0.897)		-2.505 (0.996)	-1.666 (0.952)	-0.576 (0.282)	17.97 (0.705)	6.926 (0.991)	13.391 (0.921)	7.739 (0.997)	Cannot reject H_o	I(1)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

Table 5.11. Panel unit root tests for variables on first difference for business purposes from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran & Shin (IPS) W-stat**		**ADF - Fisher Chi-Sq**		**PP - Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend		
Number of tourists	**-16.775 (0.000)**	**-11.267 (0.000)**	-	**-11.580 (0.000)**	**-16.419 (0.000)**	**-10.230 (0.000)**	**196.38 (0.000)**	**119.049 (0.000)**	**275.838 (0.000)**	**174.654 (0.000)**	Reject H_o	I(0)
FDI	**-11.412 (0.000)**	**-5.573 (0.000)**	-	**-7.556 (0.00)**	**-5.649 (0.000)**	**-1.473 (0.009)**	**66.533 (0.000)**	**100.761 (0.000)**	**83.681 (0.000)**	**123.029 (0.000)**	Reject H_o	I(0)
Cost of travel	**-10.887 (0.000)**	**-9.631 (0.000)**	-	**-6.131 (0.000)**	**-7.512 (0.000)**	**-5.427 (0.000)**	**82.106 (0.000)**	**63.784 (0.000)**	**81.144 (0.000)**	**82.592 (0.000)**	Reject H_o	I(0)
Origin income	**-7.3626 (0.000)**	**-10.698 (0.000)**	-	**-4.59 (0.000)**	**-8.507 (0.000)**	**-5.847 (0.000)**	**79.585 (0.000)**	**71.256 (0.000)**	**93.937 (0.000)**	**93.616 (0.000)**	Reject H_o	I(0)
Trade openness	**-10.008 (0.000)**	**-10.137 (0.000)**	-	**-5.014 (0.000)**	**-7.344 (0.000)**	**-6.825 (0.000)**	**85.949 (0.000)**	**85.462 (0.000)**	**123.615 (0.000)**	**133.054 (0.000)**	Reject H_o	I(0)
Cost of living at destination	**-4.878 (0.000)**	**-2.45550 0.0070**	-	**-1.787 (0.037)**	**-5.988 (0.000)**	**-3.668 (0.000)**	**73.312 (0.000)**	**61.063 (0.000)**	**90.535 (0.000)**	**84.387 (0.000)**	Reject H_o	I(0)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

Panel data unit root tests were applied to all the variables of the model on level as well as their first differences. Panel unit root tests results are reported in Tables 5.10 and 5.11. The outcomes of the unit root tests showed that some variables were stationary I(0) on level: number of tourists, human rights, transport costs, FDI, global health risks and capital investment in the tourism sector. By contrast, Saudi income, origin countries income, trade openness and cost of living at the destination variables were non-stationary on levels, but stationary on first differences, I (1). Based on these results, the cointegration relationship between the number of business tourist arrivals as a dependent variable and all the independent variables could be examined. This is discussed in the next section.

5.3.4. Business tourism demand cointegration test

In the previous section, it was noted that the unit root test results showed that some variables were non-stationary on their levels but were integrated (of order 1) and stationary on their first difference. These variables can also be cointegrated if one or more stationary linear combinations exist among them. If these variables are cointegrated, they have a stable long-run or equilibrium linear relationship. The data were tested with Kao and Pedroni cointegration tests, because Gutierrez (2003) indicated that when a small number of observations are in the panel, the results of Kao (1999) and Pedroni (1999) panel tests have more power. In addition, both tests have a null hypothesis of no cointegration (da Silva et al., 2018).

Since the panel data in this study contained a large number of independent variables and a small number of observations in the time dimension (T=20), the panel regression model was estimated in four specifications [6], shown in Table 5. 12. This approach has been used in previous studies (Barman & Nath, 2019; Lorde et al., 2016; Viljoen et al., 2019).

[6] The first specification shown in column 2 includes income of both the origin and destination countries, cost of travel, human rights and political risk. The second specification shown in column 3 includes income of both the origin and destination countries, cost of travel, global health risk and temperature. The third specification in column 4 includes economic factors that are the income of both the origin and destination countries, cost of travel, cost of living at the destination, capital investment in the tourism sector, trade openness and FDI. The fourth specification shown in column 5 includes the income of both the origin and destination countries, cost of travel, and Saudi Arabia prosperity.

Table 5.12. Results of panel cointegration tests for business tourism demand model for data from 2000 to 2019

Cointegration tests **Null hypothesis (H_0) of both panel Kao and Pedroni test is no cointegration**				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Kao test **ADF**	Test statistic (P-values) **-2.417** **(0.007)**	Test statistic (P-values) **-2.391** **(0.008)**	Test statistic (P-values) **-2.566** **(0.005)**	Test statistic (P-values) **-2.808** **(0.002)**
Pedroni Test				
H_0: common AR coefficients (within dimension)				
Statistic				
	Test Statistic (P-values)	Test Statistic (P-values)	Test Statistic (P-values)	Test Statistic (P-values)
Panel v	-2.783 (0.973)	-0.778 (0.781)	-0.487 (0.687)	-1.416 (0.926)
Panel rho	3.220 (0.9994)	0.457 (0.6757)	0.950 (0.8312)	1.219 (0.887)
Panel PP	**-3.712** **(0.000)**	**-6.189** **(0.000)**	**-10.944** **(0.000)**	**-5.900** **(0.000)**
Panel ADF	**-2.977** **(0.001)**	**-6.011** **(0.000)**	**-7.948** **(0.000)**	**-5.353** **(0.000)**
Weighted				
Panel v	-3.608 (0.998)	-1.897 (0.971)	-1.679 (0.953)	-0.999 (0.992)
Panel rho	3.711 (0.999)	0.189 (0.575)	0.787 (0.785)	0.856 (0.804)
Panel PP	**-5.723** **(0.000)**	**-5.737** **(0.000)**	**-12.859** **(0.000)**	**-11.215** **(0.000)**
Panel ADF	**-5.219** **(0.000)**	**-5.824** **(0.000)**	**-8.867** **(0.000)**	**-6.183** **(0.000)**
H_1: individual AR coefficients (between dimensioning)				
Group rho	4.942 (0.942)	2.008 (0.977)	2.218 (0.986)	2.683 (0.996)
Group PP	**-9.699** **(0.000)**	**2.008** **(0.977)**	**-18.298** **(0.000)**	**-12.519** **(0.000)**
Group ADF	**-4.583** **(0.000)**	**-6.271** **(0.000)**	**-8.729** **(0.000)**	**-6.828** **(0.000)**

Source: Author's own calculations using EViews. P-values in parentheses. Figures in **bold** indicate cointegration at 5%.

It can be seen from the results of Pedroni's (1999) panel cointegration test shown in Table 5.12 that some of the p-values for the panel v-statistic, panel rho-statistic, and group rho-statistic were greater than 0.05. For the panel PP statistic, panel ADF statistic, group PP-statistic, and group ADF-statistic, the p-values were smaller than 0.05. In terms of whether there is a long run cointegration relationship among the variables, the statistical result was inconclusive. Kao's residual cointegration test was then used to examine the long-run relationship. In the statistical results, a Kao p-value smaller than 0.05 indicates that the variables are cointegrated, which makes it certain that the variables are cointegrated in this study. Therefore, there is a long-run relationship between the variables and the null hypothesis can be rejected.

5.3.5. Empirical results and discussion of the business tourism models.

In the previous section, the results of the cointegration test confirmed that any combination of independent variables with dependent variables were cointegrated, providing support for the estimation of the model as an ARDL model.

This section presents the results of the ARDL estimator for business tourism demand in Saudi Arabia. The panel data contained cross-sectional data covering 11 origin countries from 2000 to 2019. Panel ARDL was applied. This model was considered appropriate for this study since the variables were integrated on I(0) and I(1), T was larger than N, and the sample size was small (Nyasha & Odhiambo, 2014).

5.3.5.1. Estimate ARDL models.

The business tourism panel sample covered more years than the cross-sample units. The variables in the model were integrated at orders zero and one, thereby reinforcing the choice of panel ARDL for model estimation. The dependent variable was the number of business tourist arrivals from origin i to destination j. The independent variables were origin country income, income of the destination country, cost of living, cost of travel, investment in the tourism sector at the destination, trade openness, FDI, human rights, political risks, temperature, and destination prosperity.

Results and discussion

Comparing relatively small observations to a large number of explanatory variables may lead to ARDL being less reliable. Therefore, researchers must restrict the number of independent variables and estimate models with different sets of independent variables, as this can reject the null hypothesis of no cointegration at the 1 percent level of significance. In order to identify the optimal lag length for each of the underlying variables in the ARDL model, it was necessary to apply model order selection criteria such as the Akaike information criterion (AIC), the Schwarz Bayesian criterion (SBC), or the Hannan-Quinn criterion (HQC). The optimal lag length was found to be 1, based on the AIC model selection criterion. The variables were mostly consistent in effect and significance, with different specifications.

Table 5.13. Results of panel ARDL for business tourism demands from 2000 to 2019

Long-run coefficients				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Variable	Coefficient Prob.*	Coefficient Prob.*	Coefficient Prob.*	Coefficient Prob.*
Cost of travel CT_{ij}	-0.429* (0.083)	-0.851*** (0.000)	-1.62*** (0.000)	-0.633*** (0.0000)
Cost of living at the destination P_{JI}	-	-	-0.261*** (0.007)	-
Trade openness $TADE_{ji}$	-	-	1.440*** (0.000)	-
Saudi income ID_J	0.283*** (0.000)	1.141*** (0.015)	0.236 (0.686)	1.168*** (0.000)
Origin income IO_I	0.717*** (0.000)	0.940** (0.046)	0.914*** (0.000)	0.749** (0.084)
FDI FDI_{ji}	-	-	0.012 (0.892)	-
Capital investment. $INVEST_J$	-	-	0.403*** (0.000)	-
Non-economic factors				
Prosperity index PI_J	-	-	-	0.294*** (0.000)
Global health risks HR_J	-	-0.119*** (0.023)	-	-
Political Risk $PRISK_J$	-0.748*** (0.000)	-	-	-
Relative temp. TEM_{ij}		-1.117 (0.715)	-	-
Human rights index HI_J	1.128*** (0.000)	-	-	-
Short-run coefficients				
ECT_{t-1}	-0.445*** (0.000)	-0.533*** (0.00)	-0.789*** (0.000)	-0.987*** (0.000)
D (Saudi income)	1.356 (0.389)	1.619 (0.373)	2.550 (0.328)	3.184 (0.392)
D (Origin income)	1.389 (0.576)	1.447 (0.648)	0.734 (0.904)	1.742 (0.876)
D (Transport costs) t-1	-0.773 (0.141)	-0.3260 (0.4069)	-2.118*** (0.031)	-0.253 (0.758)
D (Trade openness)	-	-	1.010 (0.145)	
D (Cost of living at destination)	-	-	-1.002 (0.760)	-
D (FDI))	-	-	-0.135 (0.892)	-
D (Capital investment)	-	-	0.260 *** (0.000)	-
D (Prosperity)	-	-	-	1.121 (0.255)

D (Political risks)	-0.087 (0.196)	-	-	-
D (Global health risks)		0.027 (0.508)	-	-
D (Relative temp.)	-	3.411 (0.176)	-	-
D (Human rights index)	0.530*** (0.000)	-	-	-
Constant	0.445 (0.680)	-5.370 (0.018)	11.890 (0.000)	-14.417 (0.002)
No. of Observations	209	209	209	121

Note: *** 1% significant, **5% significant, and * 10% significant. Model selection method: Akaike information criterion (AIC).

Table 5.13 present the long- and short-run models obtained from the panel ARDL. The coefficient of the error correction term ECT_{t-1} indicates high adjustment speed to the steady-state equilibrium. For all models in the sample, the error correction term had the expected sign and was statistically significant. Its value ranged from -0.44 to -0.98 for the sample, indicating a faster rate of equilibrium adjustment. This coefficient was negative and statistically significant. Any shock to the tourist arrivals equation was adjusted by almost 0.44, 0.53, 0.78, and 0.98. Thus, there were long-run relationships between business tourism demand and its determinants. Another significant result was the error correction term, which was significant, negative, and less than unity. Therefore, the variables were cointegrated. As indicated in Table 5.13, this condition was satisfied in the model, implying that a long-run relationship existed between all of the model's variables. Additionally, it reveals that adjustment from the short-run to the long-run equilibrium path occurred at a rate of 0.44, 0.53, 0.88, and 0.98 respectively.

Economic factors

The importance of the long-run income of both destination and origin countries was confirmed. The long-run estimation shows that the income of the origin and destination countries is important for explaining business tourist flows in all the regressions models. As the theoretical model predicts, they have a positive impact. Therefore, inbound business tourism to Saudi Arabia is likely to increase with the intensity of an economic relationship between two states. This result is consistent with previous studies, such as Tsui et al. (2018), and Kulendran and Divisekera (2006), which found that overall the origin country's real income is a significant factor impacting business travel. In contrast, this result is inconsistent with Senadeerage (2020), who found that the income of origin countries does not significantly impact business tourism demand in context of Sri Lanka.

It should also be noted that the significant impact of destination economic variables on business tourist arrivals found in this current study is not consistent with prior research that has used the gravity model to investigate business international tourist flows. This includes Tsui et al. (2018), who suggested that destination economic variables do not play a significant role in influencing inbound business travel flows. This may be because, Saudi Arabia, as the focus of this current study, is one of the twenty largest global economies, has a strong business environment, and has the largest oil markets, supported by its geographical and cultural position between the three continents. This attracts business travel.

Table 5.13 also presents the long-run and short-run impact estimated regression coefficient of the cost of living at the destination (tourism price) on business tourism demand. The tourism price coefficient was negative, as expected and statistically significant in the long-run equation. This shows that a 1 percent increase in the tourism demand led to a 0.26 percent decrease in business tourism demand, assuming all other factors remain constant in our sample countries. This means that the demand for business tourism from origin countries to Saudi Arabia decreases with increasing tourism prices in Saudi Arabia. This implies that tourists are sensitive to changes in the price level. This result confirms the earlier findings of Durbarry (2008), Eilat and Einav (2004), and Vietze (2012), although it is not significant in the short run. Several previous studies (e.g., Cracolici and Nijkamp, 2009; Divisekera, 2003; Narayan, 2004) indicated that tourism price variables affected the number of international tourists visiting a destination (including business tourists). However, Chow and Tsui (2019), Kulendran and Witt (2003b), and Tsui et al. (2018) argued that the cost of living in the destination is far less likely to affect business travel volume than income and trade volumes. In this study of Saudi Arabia, the significantly smaller size of price elasticities indicated that, despite disparities in the cost of living, tourism demand in underdeveloped nations such as Saudi Arabia was significantly less price-sensitive than demand in industrialised countries.

The estimated coefficient of cost of travel was negative and significant. This indicates that the lower the cost of travel to Saudi Arabia from the country of origin, the greater the increase in business tourism demand. One percent increase in the cost of travel between the origin country and Saudi Arabia decreased the business tourism demand on (0.42, 0.85, 1.62, and 0.63) by average 0.88 percent and other things held constant. Consistent with this, Gholipour and Foroughi (2019), Kulendran and Wilson (2000a), Kulendran and Witt (2003a), and Tsui et al. (2018) showed that increases in travel costs have a negative impact on business travel.

This study's results show that capital investment in the destination country tourism sector has a positive impact on business tourism demand in the long and short run. One percent increase in tourism investment increased business tourism demand by 0.40 percent in the long run, ceteris paribus. Investment in the tourism and travel sectors may lead to improved infrastructure, goods and services for meetings, conferences, exhibitions, and trading activities.

This currently study found that the coefficient of FDI had a positive but insignificant effect on the demand for business travel and had the correct sign. In contrast, Bezuidenhout and Grater (2016), Kulendran and Wilson (2000a), and Tang et al. (2007) demonstrated that FDI has a statistically significant positive impact on business travel.

The results indicate that trade openness had a statistically significant and positive impact on business tourism in long run. International trade has an impact on international business travel to Saudi Arabia, meaning that business travel levels are higher in countries with more international trade. This result is consistent with many earlier tourism demand studies, including Kulendran and Wilson (2000a), Kulendran and Witt (2003b), Okafor et al. (2023), Selvanathan et al. (2012), Smith and Toms (1978), Tsui et al. (2018), and Turner and Witt (2001). In the context of Saudi Arabia, however, the literature has ignored the relationship between trade and business tourism demand. Previous studies examined the impact of trade on the demand for total number of tourists (Jamel, 2020) and religious tourism (Shaheen, 2019; Triki, 2019). While Jamel (2020) found trade had a negative influence on tourism, Shaheen (2019) and Triki (2019) found trade and demand for religious tourism had a positive and significant relationship.

Non-economic factors

The political risks coefficient had the expected signs, with negative and significant impact on business tourism demand in the long run indicating that political risks negatively and significantly affect business tourism demand in Saudi Arabia. Gholipour and Foroughi (2020) found that there is only an insignificant relationship between political stability and business travel, and Senadeerage (2020) found war had a negative and significant effect on business tourism demand in Sri Lanka.

This study found that the estimated coefficient for relative temperature had a negative sign and was insignificant in the long and short run. The negative sign may relate to the hot temperature in Saudi Arabia. A 1percent increase in ratio of the origin country temperature to destination country temperature decreased business tourism demand by 1 percent, all other things held constant in long run. The coefficient of the short-run impact was positive and insignificant. This implies that relative temperature factor was not an important factor in terms of business tourism demand.

The estimated coefficient of destination prosperity had a positive and significant impact on business tourism demand in Saudi Arabia and explains the direct impact on business tourism demand. Improved living standards and the prosperity of Saudi residents would increase the number of tourists, as explained earlier in relation to the religious estimation results. This is a novel outcome since, to the best of our knowledge, no other study has investigated the relationship between business tourism demand and the destination's prosperity.

The coefficient of global health risks had a negative and significant association with business tourism demand. This result is consistent with prior studies (Karabulut et al., 2020; Uzuner & Ghosh, 2020; Zhong et al., 2021). An increase in global health risks would lead to decreases in business tourism demand, other things being held constant.

As seen in Table 5.13, business tourism demand to Saudi Arabia was influenced positively by the human rights index in the long and short run. As stated in Section 5.2, Saudi Arabia needs to maintain its image as a safe and secure destination and continue to implement initiatives to enhance human rights. This result aligns with the work of Senadeerage (2020), who confirmed that civil liberty (political freedom) is a crucial factor in the demand for business tourism.

Across the four models tested in this study using the panel ARDL estimator, the results showed the consistently positive impact of GDP per capita in Saudi, GDP per capita in the origin countries, trade openness, and capital investment in the destination tourism sector on business tourism demand. By contrast, transport costs, global health risks, and the cost of living at the destination had a negative impact on business tourism demand.

5.3.5.2 Panel regression model estimates

As mentioned earlier, due to uncertainties over the validity of unit root and cointegration tests in small samples (T=20 in this thesis), this study conducted panel regression model estimates to investigate the factors that influence the business tourism arrivals. It assumed that all variables were stationary. In order to choose between POLS, RE, and FE, diagnostic tests were undertaken. Table 5.14 shows the results of the Chow test, the Lagrange multiplier test, and the Hausman test, completed to test and select the most appropriate panel data model.

Model specification test

The Chow test was conducted to compare the POLS model against the FE model. The Chow test results suggested that the FE model was the most appropriate. The Lagrange multiplier-test compared the POLS model to the RE model; the Hausman-test compared the FE model to the RE model. Again, these test results (see Table 5.14) indicated that the FE model was the most appropriate. The JB test was utilised to assess the normality of the residuals. Given its value was more than 5 percent, the residual was normally distributed. A cross-sectional dependence test was applied to check for the absence of cross-section dependence. Since its value was greater than 5 percent, the absence of cross-section dependence was confirmed. Table 5.14 presents the results of a slope homogeneity test that was conducted in this study. The null hypothesis could not be rejected, and it was determined that slope coefficients were homogeneous. It was concluded that heterogeneity did not exist across samples.

Table 5.14. Specification tests for the panel regression method to choose the most appropriate model between POLS, FE and RE

Specification tests	Statistic (Prob.)	Choose between	Decision (selection)
Chow test	7.673 (0.000)	POLS /FE Null hypothesis: POLS is more appropriate to estimate panel than FE.	FE Reject the null hypothesis.
Lagrange multiplier tests (Breusch-Pagan – LM test)	30.361 (0.000)	POLS /RE Null hypothesis: POLS is more appropriate to estimate panel than RE.	RE Reject the null hypothesis.
Hausman test	33.600 (0.000)	FE/RE The preferred model is RE .	FE Reject the null hypothesis.
Preliminary tests			
Slope homogeneity test	$\hat{\Delta}$ = 5.915 (0.219) $\hat{\Delta}_{adj}$ = 17.163 (0.739)	Null hypothesis of the test is: slope coefficients are homogenous.	Cannot reject the null hypothesis of slope homogeneity. Thus, slope coefficients were homogenous in cointegration equations.
Cross-section dependence: **Breusch-Pagan LM**	0.562 (0.222)	Null hypothesis: there is no cross-section dependence.	Cannot reject the null hypothesis. Thus, there is no cross-sectional dependence in panel data analysis.
Pesaran scaled LM	0.739 (248)		
Bias-corrected scaled LM	0.137 (0.554)		
Pesaran CD	0.122 (0.902)		
Normal distribution JB probability	0.986 (0.610)	Null hypothesis: residuals are normally distributed.	Cannot reject the null hypothesis. Thus, residuals are normally distributed.

Source: Author's own calculations using EViews.
Note: $\hat{\Delta}$ *and* $\hat{\Delta}_{adj}$ tests are a modified version of the Swamy (1970) test proposed by Pesaran and Yamagata (2008). In both cases, slope homogeneity is the null hypothesis.

The results of the FE model are presented in Appendix C, showing that it was consistent with dynamic estimation results. Cultural affinity factors had negative and insignificant impact on business tourism demand, implying that cultural affinity was not an important factor in business tourism demand to Saudi Arabia. In FE models, the coefficient of determination R^2 shows how much of the observed variance in the dependent variable is explained by the model. The goodness of fit using R^2 was high on the FE model, which suggests that the estimated predictors explained 77 percent of the variation in business international tourism arrivals to Saudi Arabia. The p-value of the models (Prob >F=0.000) was statistically significant, which means that the estimated predictors reliably predicted international tourism arrivals to Saudi Arabia for business purposes.

5.4. Visiting friends and relatives (VFR) Tourism

In the previous section, business tourism demand was estimated. This section offers an estimate of the VFR tourism demand in Saudi Arabia. It presents the descriptive statistics, correlation matrix, panel unit root tests, results and discussions of VFR tourism demand models.

5.4.1. Descriptive statistics for VFR tourism demand

The data needed to be thoroughly evaluated before estimating. The essential features of the data in the study were described using descriptive statistics. The descriptive statistics of dependent and independent variables are shown in Table 5.15. This table summarises the descriptive statistics, including mean, median, minimum, maximum and standard deviation of all the variables used in the empirical analysis of VRE tourism demand from 2000 to 2019. The dependent variable was VFR tourist arrivals to Saudi Arabia.

Table 5.15. Descriptive statistics for international VFR tourism data from 2000 to 2019

	Number of VFR tourists	Cost of travel	Cost of living at destination	International Saudi students	Origin income	Relative temp.
Mean	148,685	180,942.10	3.095	133,689	14,069.85	1.91
Median	48,638	176,086.00	0.637	139,914	4,556.43	0.95
Maximum	1,048,464	306,234.20	25.982	199,285	69,679.09	91.74
Minimum	2,431	319.56	0.000	42,806	720.36	0.44
Standard deviation	217,298	95,900.16	6.177	49,082	18,439.30	9.52

Source: Author's own calculations using EViews.

The descriptive statistics of other variables (Saudi income, destination prosperity, political risks, global health risks, human rights, and capital investment in the tourism sector) were provided in Table 5.1 for religious purposes. The same data was used for all models regardless the purpose of visit.

Table 5.15 presents descriptive statistics for the variables used in the analysis of international VFR tourism from 2000 to 2019. The overall average number of VFR tourists was 148,685, ranging from a minimum of 2,431 tourists to a maximum of 1,048,464. The results in this table show, on average, a higher value for the cost of travel (180,942.10), number of arrivals in international tourism (148,685), and international Saudi students (133,689).

5.4.2. VFR tourism demand correlation matrix

While the previous section reported on the descriptive statistics of the variables used in the empirical investigation, this section presents the matrix showing the correlation between independent variables. To test the null hypothesis that there is no correlation among the independent variables, the multicollinearity (approximate linear relationships between explanatory variables) test was employed.

Table 5.16. VFR pairwise correlation: A Pearson correlation matrix between explanatory variables

	Cost of travel	Relative temp.	Political risks	Prosperity	Saudi students overseas	Human rights	Saudi income	Origin income	Global health risks	Relative price	Capital investment
Cost of travel	1										
Relative temp.	-0.008	1									
Political risks	0.079	0.105	1								
Prosperity	-0.007	0.072	0.541	1							
Saudi students overseas	-0.015	-0.040	-0.668	-0.586	1						
Human rights	-0.086	-0.060	-0.419	-0.026	0.213	1					
Saudi income	-0.211	-0.047	-0.470	-0.491	0.606	0.096	1				
Origin income	-0.609	-0.055	-0.048	-0.038	0.041	0.037	0.238	1			
Global health risks	-0.12	-0.039	-0.465	0.096	0.053	0.196	-0.089	0.015	1		
Cost of living at destination	-0.435	-0.105	0.077	0.059	-0.048	-0.064	0.097	0.592	-0.038	1	
Capital investment	0.004	-0.045	-0.393	-0.637	0.575	0.019	0.4331	0.031	0.090	-0.045	1

Source: Author's own calculations using EViews.

The correlation matrix of all the variables in this model did not suggest a multicollinearity problem (see Table 5.16).

5.4.3. VFR tourism demand panel unit root tests

The previous section outlined the test of multicollinearity among explanatory variables using a pairwise correlation matrix. In this section, stationarity test results are presented for the variables that were used in these models before regression analysis was carried out. This study conducted the panel unit root test for both dependent and independent variables. The null hypothesis being tested was that the data contains a unit root.

Table 5.17. Panel unit root tests for variables on level for VFR purposes from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran & Shin (IPS) W-stat**		**ADF - Fisher Chi-Sq**		**PP - Fisher Chi-Sq**		**Decision**	**Order of integratio n**
Variables	individual intercept	individual intercept & trend	-	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept &Trend		
The number of tourists	**-6.445 (0.000)**	**-4.544 (0.000)**	**-**	**-3.015 (0.001)**	**-3.690 (0.000)**	**-4.301 (0.000)**	**65.919 (0.000)**	**72.824 (0.000)**	**71.43 (0.000)**	**71.436 (0.000)**	Reject H_o	I(0)
Cost of living at destination	-1.905 (0.971)	3.498 (0.999)	-	-2.348 (0.990)	-1.594 (0.944)	-3.678 (0.999)	28.717 (0.532)	37.059 (0.175)	14.469 (0.992)	19.770 (0.922)	Cannot reject H_o	I(1)
Origin income	-1.501 (0.933)	**-2.147 (0.015)**	-	**-2.752 (0.002)**	-0.686 (0.753)	-0.930 (0.176)	29.799 (0.475)	**49.068 (0.015)**	28.712 (0.532)	32.681 (0.336)	Cannot reject H_o	I(1)
Transport costs	**-27.444 (0.000)**	**-17.023 (0.000)**	-	-1.027 (0.152)	-3.895 (0.000)	-3.234 (0.999)	11.640 (0.999)	9.003 (0.999)	16.174 (0.981)	9.038 (0.999)	Cannot reject H_o	I(1)
Saudi students overseas	**-1.984 (0.023)**	**-1.947 (0.025)**	-	**-3.557 (0.000)**	**-4.273 (0.000)**	**-1.220 (0.888)**	**62.884 (0.000)**	12.967 (0.997)	**6.472 (0.000)**	9.074 (0.999)	Reject H_o	I(0)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

It is worth noting that the panel unit root tests were conducted on levels and first differences of the variables, Saudi income, destination prosperity, political risks, global health risks, human rights and capital investment in the tourism sector in the first section (as shown in Tables 5.3 and 5.4). The same data were used for all models, regardless of the purpose of the visit, as the variables relate to the destination country.

Table 5.17 presents the results of the unit root test on level from various methods. The null hypothesis is the presence of unit root I(1) and could not be rejected for variables Saudi income, income of the origin country, transport costs, and relative price. This means these variables were not stationary on the level. The null hypothesis could be rejected in the following variables: number of VFR tourist arrivals to Saudi Arabia, political risks, destination prosperity, Saudi overseas students, global health risks, and human rights, and capital investment in the tourism sector. This means these variables were stationary I(0) on the level. The results indicate that the variables of this model had different integrated orders I(0) and I(1).

Table 5.18. Panel unit root tests for variables on first difference for all country models for VFR purposes from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran& Shin (IPS) W-stat**		**ADF - Fisher Chi-Sq**		**PP - Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend		
The number of tourists	**-16.770** **(0.000)**	**-16.775** **(0.000)**	**-**	**-11.580** **(0.000)**	**-16.419** **(0.000)**	**-16.419** **(0.000)**	**196.348** **(0.000)**	**196.348** **(0.000)**	**275.838** **(0.000)**	**275.838** **(0.000)**	Reject H_o	I(0)
Origin Income	**-7.362** **(0.000)**	**-7.151** **(0.000)**	**-**	**-4.593** **(0.000)**	**-8.507** **(0.000)**	**-7.677** **(0.000)**	**132.580** **(0.000)**	**112.928** **0.0000**	**374.937** **(0.000)**	**113.754** **(0.000)**	Reject H_o	I(0)
Saudi students overseas	**-6.11830** **(0.000)**	**-7.659** **(0.000)**	-	-2.1839 (0.0145)	-1.215 (0.112)	-4.057 (0.000)	31.887 (0.372)	**60.87** **(0.000)**	29.897 (0.470)	**59.540** **(0.001)**	Reject H_o	I(0)
Transport costs	**-12.887** **(0.000)**	**-28.644** **(0.000)**	-	**-6.131** **(0.000)**	**-7.587** **(0.000)**	**-9.107** **(0.000)**	**104.444** **(0.000)**	**107.949** **(0.000)**	**103.244** **(0.000)**	**130.956** **(0.000)**	Reject H_o	I(0)
Relative temp.	**2.466** **(0.932)**	**-11.229** **(0.000)**	-	**-10.959** **(0.000)**	**-9.647** **(0.000)**	**-16.5783** **0.0000**	**131.610** **(0.000)**	**220.901** **0.0000**	**275.589** **(0.000)**	**294.791** **0.0000**	Reject H_o	I(0)
Cost of living at destination	**-6.360** **(0.000)**	**-4.640** **(0.000)**	-	**-3.525** **(0.000)**	**-6.505** **(0.000)**	**-5.3095** **(0.000)**	**91.730** **(0.000)**	**90.858** **(0.000)**	**100.293** **(0.000)**	**104.451** **(0.000)**	Reject H_o	I(0)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

The panel unit root tests were conducted on the first differences of the variables, as shown in Table 5.19. The null hypothesis of a unit root was rejected in all variables on the first difference I(0). Overall, as illustrated in Tables 5.18 and 5.19, panel unit root tests were performed on the levels and the first differences of all the variables to check the level of integration of the model's variables. The test results show that some variables were not stationary on the level but were integrated into their first differences.

5.4.4. VFR tourism demand cointegration test

As noted in the previous section, the unit root test indicated that some variables were non-stationary on their levels and integrated at I(1), and stationary on their first difference. Therefore, a cointegration test could be considered. This study applied the panel cointegration test of Kao and Pedroni, and the null hypothesis was no cointegration among the variables in the model.

Table 5.19. Results of the panel cointegration tests

Cointegration tests Null hypothesis (H_0) of both Panel Kao and Pedroni Test is no cointegration				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Kao test ADF	Test statistic (P-values) **-5.660** **(0.000)**	Test statistic (P-values) **-6.119** **(0.000)**	Test statistic (P-values) **-7.353** **(0.000)**	Test statistic (P-values) **-4.814** **(0.000)**
Pedroni test				
	H_1: Common AR coefficients (within dimension)			
	Test statistic (P-values)	Test statistic (P-values)	Test statistic (P-values)	Test statistic (P-values)
Panel v	-1.236 (0.891)	-0.602 (0.726)	-0.467 (0.679)	-0.992 (0.839)
Panel rho	1.087 (0.861)	1.228 (0.888)	0.076 (0.530)	0.728 (0.767)
Panel PP	-6.241 (0.000)	-5.616 (0.000)	-5.647 (0.000)	-4.505 (0.000)
Panel ADF	-6.002 (0.000)	-4.876 (0.000)	-5.400 (0.000)	-3.855 (0.000)
Weighted				
Panel v	-2.304 (0.9894)	-1.989 (0.976)	-1.146 (0.874)	-1.376 (0.915)
Panel rho	2.004 (0.977)	1.663 (0.951)	0.599 (0.725)	1.127 (0.863)
Panel PP	-7.309 (0.000)	-7.191 (0.000)	-6.000 (0.000)	-5.256 (0.000)
Panel ADF	-6.424 (0.000)	-4.792 (0.000)	0.567 (0.000)	-3.790 (0.000)
	H_1: Individual AR coefficients (between dimension)			
Group rho	**3.318** **(0.999)**	**3.279** **(0.995)**	**2.220** **(0.968)**	**2.277** **(0.988)**
Group PP	**-10.989** **(0.000)**	**-11.797** **(0.000)**	**-8.611** **(0.000)**	**-7.461** **(0.000)**
Group ADF	**-7.185** **(0.000)**	**-5.752** **(0.000)**	**-6.448** **(0.000)**	**-4.232** **(0.000)**

Source: Author's own calculations using EViews. P-values are shown in parentheses. **Bold** denotes that the test indicates cointegration at 5%. *Note*: H_o is no cointegration; p-value < 0.05 indicates the rejection of the null hypothesis.

Since the panel data in this study contained a large number of independent variables and a small number of observations in the time dimension (T=20), the cointegration tests and estimation were conducted in four different specifications models.[7]

Based on the results of the Pedroni tests (including panel PP, panel ADF, group PP, and group ADF), and the Kao cointegration tests, as shown in Table 5.19, the null hypothesis of no cointegration could be rejected. Therefore, there was a long-run relationship between the variables providing support for the estimation of the model as an ARDL.

5.4.5. Empirical results and discussions of VFR tourism demand models

As noted, the results of the cointegration test provided support for the estimation of the model as an ARDL model. Therefore, this section presents the results of the ARDL estimator for VFR tourism in Saudi Arabia, as well as tests of model validity. A panel regression model estimator also added robustness to the results.

5.4.5.1. Estimate ARDL models.

In chapter four, the specifications of the model were explained. Dynamic model optimal lag length was selected based on the AIC model criterion, which was taken as 1. It is worth mentioning that variables were mostly consistent in effect and significance, with different specifications.

Table 5.20. Panel ARDL results for VFR tourism from 2000 to 2019

Long-run coefficients				
Variable	**Model 1** Coefficient Prob.*	**Model 2** Coefficient Prob.*	**Model 3** Coefficient Prob.*	**Model 4** Coefficient Prob.*
Cost of travel CT_{ij}	-1.051*** (0.000)	-0.650*** (0.000)	-0.383*** (0.000)	-0.892*** (0.000)
Cost of living at destination P_{IJ}	-	-0.178 (0.253)	-	-
Saudi income ID_J	1.576*** (0.000)	1.242*** (0.000)	1.454*** (0.000)	1.953*** (0.000)
Origin income IO_I	1.080*** (0.000)	0.713*** (0.000)	0.977*** (0.000)	1.068*** (0.000)
Capital investment $INVEST_J$	-	1.616*** (0.000)	-	-

[7] The first specification model shown in column 2 includes the income of both the origin and destination countries, cost of travel, human rights, and political risks; the second model shown in column 3 includes economic factors that are the income of both the origin and destination countries, cost of travel, cost of living at the destination and capital investment in the tourism sector; the third specification model shown in column 4 includes the income of origin country, the income of Saudi Arabia, cost of travel, and the destination prosperity index; the fourth specification model shown in column 5 includes the income of both the origin and destination countries, cost of travel, global health risks, relative temperature, and Saudi students studying overseas.

Prosperity index PI_J	-	-	0.552** (0.076)	-
Global health risks HR	-	-	-	-0.036 (0.119)
Political risks $\mathbf{PRISK}_J$	-0.3724*** (0.0000)	-	-	-
Human rights Index HI_J	0.315 (0.449)	-	-	-
Relative temp. TEM_{JI}	-	-	-	0.1860 (0.3632)
Saudi students overseas $\mathbf{OVESTU}_{ij}$	-	-	-	0.369*** (0.000)
Short-run coefficients				
$\mathbf{ECT}_{t-1}$	-0.909 (0.000)	-0.805 (0.000)	-0.802 (0.000)	-0.945 (0.000)
D (travel costs)	-0.774** (0.021)	-0.067 (0.559)	-1.922 (0.338)	-0.291 (0.685)
D (cost of living at the destination	-	0.533 0.600	-	-
D (Saudi income)	0.768 (0.501)	1.325*** (0.001)	3.506 (0.122)	2.749 (0.260)
D (origin income)	1.132 (0.833)	-0.310 (0.931)	2.58 (0.526)	0.820 (0.814)
D (international students)	-	-	-	0.787 (0.191)
D (capital investment)	-	0.341*** (0.020)	-	-
D (human rights)	1.2980*** (0.000)			
D (prosperity)	-	-	2.253 (0.443)	-
D (political risks)	-0.685*** (0.007)	-	-	-
D (global health risks)	-	-	-	-0.014 (0.759)
D (relative temp.)	-	-	-	-0.3425 (0.9525)
Constant	4.055 (0.000)	-20.232 (0.000)	-8.040 (0.000)	-10.258 (0.000)

Source: Author's own calculations using EViews. *Note*: *** 1% significant, ** 5% significant and * 10% significant.

In Table 5.20, the error correction coefficient ECT_{t-1} was -0.909, -0.805, -0.802 and -0.945 for the four models respectively, with negative signs and statistical significance. This confirms the existence of cointegration and a short-term equilibrium relationship between the variables used towards a long-term equilibrium relationship. This means that dis-equilibrium in tourism demand in the short term was adjusted by almost 90 percent, 80 percent, and 94 percent within the first year and that the system would return to equilibrium in the long term. As stated in the literature review chapter, the factors of VFR tourism demand have rarely been explored in Saudi Arabia tourism studies. In addition to economic factors, this study estimated non-economic factors to identify those that impact VFR tourism demand.

Economic factors

The results for the model of demand for VFR tourism in Saudi Arabia are provided in Table 5.20. As can be seen, GDP per capita in Saudi is significant in all the models with a positive sign. The elasticity in GDP per capita in Saudi in the estimated models ranges from 1.24 to 1.95. GDP per capita in the origin countries is also significant and with a positive sign and elasticity in the estimated models ranging from 0.713 to 1.080. This indicates that VFR tourism demand in Saudi Arabia is highly sensitive to destination economic levels and development. On the other hand, travel cost is negative and significant in all the models of VFR tourism demand in Saudi Arabia, since this travel cost represents a large amount of the total travel cost. However, cost of living at the destination has a correct sign but it is not significant. This may be due to the fact that those visitors stay with friends or relatives, which reduces spending on accommodation.

The results indicate that capital investment in the in Saudi tourism sector has a positive relationship with VFR tourism demand in the long and short term. This may represent unique evidence in this study of the impact of investment in tourism demand in the destination country on VFR tourism demand. The results on the effect of public infrastructure in the tourism demand literature are mixed. For instance, Proença and Soukiazis (2005) found public investment had no impact on tourism demand in Portugal, whilst Yazdi and Khanalizadeh (2017) found tourism transport infrastructure played a key role in tourist arrivals in the US.

Non-economic factors

Political risks had a negative and significant effect on VFR tourism demand in both the long and short run in Saudi Arabia. This result is consistent with Senadeerage (2020), and Xu and Dong (2020), who found political risks in the destination country were significant factors in VFR tourism demand, and that an increase in political risk in a destination country leads to a decrease in tourism flows.

The human rights factor had a positive but statistically insignificant impact on VFR tourism demand in the long run but it was significant in the short run.

Destination prosperity had a positive and significant impact on VFR tourist arrivals to Saudi Arabia in the long run, meaning an increase in destination prosperity leads to an increase in VFR tourist flows to the destination country. This study is the first to examine the effects of destination prosperity on VFR tourism demand.

As expected, Saudi students studying overseas were positively related to VFR tourism. The estimated number of Saudi international students' elasticity was 0.37. Saudi students studying abroad may have contributed to VFR tourism when they visited their families during study periods.

Relative temperature was insignificant with a positive sign. Therefore, there is no evidence to support the hypothesis that relative temperature significantly affects VFR tourism demand in Saudi Arabia. In this study, the estimated coefficients of global health risks had a negative and significant effect on tourism demand. This is evidence of the negative impact of global health risks on tourist flows.

5.4.5.2 Estimate panel regression models

The previous section outlined the ARDL method employed in this study to examine the major determinants of international tourist arrivals to Saudi Arabia. However, since there is doubt about the reliability of unit root tests for small sample sizes, this study also considered that all the variables were stationary and used panel regression model estimators. Diagnostic tests were conducted to choose between POLS, RE, and FE as the most appropriate model.

Model specification test

As shown in Table 5.21, the probability value of the Hausman Test was $0.000 < 0.05$. As discussed previously, this means that the FE model was preferable to the RE model. The results of Lagrange multiplier tests for RE (the Breusch-Pagan LM test) led to the rejection of the null hypothesis that POLS was more appropriate than FE. Therefore, POLS was deemed not appropriate for this VFR model.

Next, the cross-sectional dependence in this model was checked. The null hypothesis of this test was that there was no cross-section dependence (correlation) in residuals. The p-value of this test was 0.996. Thus, the null hypothesis could not be rejected. Therefore, there was no exit cross-sectional dependence (correlation) in the countries analysed. This implies that a shock affecting one country does not transfer to the others and, therefore, cross-sectional dependence should not be taken into account in the estimation process.

The results of the JB normality test are also presented in Table 5.21. The null hypothesis of the normality test was that the data were normally distributed. The results indicated that the null hypothesis could not be rejected. This means that the data used in this VFR tourism demand model were normally distributed. Since the p-values of the slope homogeneity test shown in Table 5.21 are more than the 1 percent significance level, the null hypothesis, slope coefficients are homogenous, can be rejected. This means that heterogeneity did not exist across the sample and heterogeneous panel techniques should be used.

Table 5.21. Specification tests for the VFR panel regression method to choose the most appropriate model between POLS, FE and RE

Specification tests	Statistic (Prob.)	Choose between	Decision (selection)
Chow test	34.022 (0.000)	POLS /FE Null hypothesis: POLS is more appropriate to estimate panel than FE.	FE Reject the null hypothesis.
Lagrange multiplier tests (Breusch-Pagan – LM test)	126.804 (0.000)	POLS /RE Null hypothesis: POLS is more appropriate to estimate panel than RE.	RE Reject the null hypothesis.
Hausman test	17.326 (0.000)	FE/RE Null hypothesis: RE is the preferred model	FE Reject the null hypothesis.
Preliminary tests			
Slope homogeneity test	$\hat{\Delta}$ = 18.393 (0.246) $\hat{\Delta}_{adj}$ = 20.732 (0.145)	Null hypothesis: slope coefficients are homogenous.	Cannot reject the null hypothesis of slope homogeneity. Thus, slope coefficients were homogenous.
Cross-section dependence: **Breusch-Pagan LM**	1.964 (0.884)	Null hypothesis: there is no cross-section dependence.	Cannot reject the null hypothesis. Thus, there is no cross-sectional dependence in panel data analysis.
Pesaran scaled LM	0.397 (0.963)		
Bias-corrected scaled LM	1.214 (0.867)		
Pesaran CD	0.049 (0.996)		
Normal distribution **JB** **probability**	5.049 (0.800)	Null hypothesis: residuals are normally distributed.	Cannot reject the null hypothesis. Thus, residuals are normally distributed.

Source: Author's own calculations using EViews.
Note: $\hat{\Delta}$ *and* $\hat{\Delta}_{adj}$ tests are a modified version of the Swamy (1970) test proposed by Pesaran and Yamagata (2008). In both cases, slope homogeneity is the null hypothesis.

FE estimation results are provided in Appendix D. The results of FE estimation were consistent with the general panel ARDL model results. The FE panel goodness of fit test using R^2 was high in the FE model, indicating 78 percent and suggesting that the estimated predictors explain 78 percent of the variation in VFR international tourism arrivals to Saudi Arabia. The p-value of the models (Prob >F=0.000) was statistically significant, which means that the estimated predictors reliably predict international tourism arrivals to Saudi Arabia for VFR purposes. This is evident in the cultural affinity variables. Sharing a common religion and language between bilateral countries is not an important factor in VFR to Saudi Arabia. Visa restrictions have a large negative effect on the flow of VFR tourists in Saudi Arabia. These restrictions are likely to deter VFR visitors from certain countries. They will therefore reduce the flow of tourists and damage Saudi's tourism industry. In turn, this will reduce its scientific, cultural, and other such exchanges with other countries. The results re-confirm the findings of Neumayer (2010) that visa restrictions reduce travel, on average, between 52 and 63 percent.

5.5. Aggregate tourism demand (total arrivals)

There is a claim that modelling tourism demand at a disaggregate level better reflects the heterogeneity of tourism demand. Therefore, this study compares the results of tourism demand models based on individual visiting purposes (religious, VFR, and business tourism) to the results of models considered in aggregate. The same set of explanatory variables were used to determine how these factors impact disaggregate and aggregate tourism demand. In other words, to check whether different tourism types respond differently to changes in independent variables.

5.5.1. Descriptive statistics for aggregate tourism demand

The data need to be thoroughly evaluated before estimating. The essential features of the data in the study were described using descriptive statistics. The descriptive statistics of dependent and independent variables are shown in Table 5.22. This table summarises the descriptive statistics, including mean, median, minimum, maximum, and standard deviation of all the variables used in the empirical analysis of aggregate tourism demand from 2000 to 2019. The dependent variable is the total number of arrivals to Saudi Arabia.

Table 5.22. Descriptive statistics for international aggregate tourism demand from 2000 to 2019

	Number of tourists	Trade openness	Transport costs	Relative temp.	Cost of living at destination	GDP per capita in origin countries	FDI	Saudi students overseas
Mean	784,529	0.014	217,963	1.410	0.210	2,576.97	2.680	133,763
Median	684,645	0.009	198,514	0.940	0.050	2,635.19	1.240	139,914
Maximum	2,537,200	0.066	306,234	4.250	2.200	4,830.20	8.500	199,285
Minimum	50,735	0.008	119,933	0.720	-	720.36	0.210	42,806
Standard deviation	569,794	0.016	65,604	1.200	0.440	1,301.79	2.780	48,951

Source: Author's own calculations using EViews.

Table 5.22 illustrates that the majority of variables indicate a substantial variation in value over the period. The cost of living at the destination, relative temperature, and trade openness showed the lowest variability, while the total number of tourists, transport costs, and income of the origin countries showed the highest variability.

5.5.2. Aggregate tourism demand correlation matrix

This section presents the matrix showing the correlation between the independent variables used in regression models for the observation period. Table 5.23 provides a summary of the estimated coefficients of the Pearson correlation matrix between all indicators included in this model. The empirical results show that there were no multicollinearity problems while estimating the equation. Since there is no correlation issue, the investigation and estimation could continue in this instance.

Table 5.23. Aggregate tourism demand: A Pearson correlation matrix between explanatory variables from 2000 to 2019

	Transport costs	Relative temp.	Cost of living at destination	Capital investment	Global health risks	Political risks	Origin income	Saudi income	Human rights	FDI	Saudi students overseas	Trade openness	Prosperity
Transport costs	1												
Relative temp.	0.015	1											
Cost of living at destination	0.110	-0.052	1										
Capital investment	0.005	-0.592	-0.412	1									
Global health risks	-0.607	-0.004	-0.086	0.001	1								
Political risks	0.619	0.055	0.204	-0.064	-0.180	1							
Origin income	-0.055	0.674	-0.060	-0.319	0.026	-0.146	1						
Saudi income	-0.062	-0.050	-0.156	0.074	0.191	-0.398	0.157	1					
Human rights	-0.493	-0.025	-0.161	0.013	0.224	-0.464	0.090	0.219	1				
FDI	0.305	0.036	0.220	-0.060	-0.234	0.680	-0.188	-0.693	-0.512	1			
Students overseas	-0.057	-0.022	-0.116	0.030	0.054	-0.432	0.197	0.643	0.185	-0.687	1		
Trade openness	0.227	-0.118	0.092	0.017	-0.154	0.154	-0.520	-0.015	-0.097	0.076	-0.038	1	
Prosperity	-0.017	-0.006	0.133	-0.003	0.094	0.628	-0.186	-0.544	-0.072	0.681	-0.585	0.007	1

Source: Author's own calculations using EViews

5.5.3. Aggregate tourism demand panel unit root tests

In the previous section, the discussion focused on the testing of multicollinearity among explanatory variables by using a pairwise correlation matrix. In this section, test results are presented for the stationarity of the variables that were used in these models before regression analysis was carried out. This study conducted the panel unit root test for both dependent and independent variables. The null hypothesis being tested was that the data contained a unit root.

Table 5.24. Panel unit root tests for variables on level for aggregate tourism demand from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran & Shin (IPS) W-stat**		**ADF – Fisher Chi-Sq**		**PP – Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept &Trend		
The number of tourists	**-4.357 (0.000)**	-1.303 (0.096)	**-**	**-3.761 (0.000)**	-0.331 (0.370)	**-2.926 (0.001)**	**23.929 (0.046)**	**32.056 (0.003)**	**24.567 (0.039)**	**46.524 (0.000)**	Reject H_o	I(0)
Origin income	-0.114 (0.545)	-0.747 (0.772)	-	-0.213 (0.415)	-1.284 (0.900)	-2.100 (0.982)	7.389 (0.918)	6.811 (0.941)	6.714 (0.945)	6.684 (0.946)	Cannot reject H_o	I(1)
Cost of living at destination	- 0.253 (0.600)	**-3.8568 (0.000)**	-	-0.387 (0.349)	- 0.452 (0.675)	-0.501 (0.306)	14.330 (0.424)	20.543 (0.114)	5.418 (0.979)	23.467 (0.053)	Cannot reject H_o	I(1)
Cost of travel	-1.601 (0.945)	-1.013 (0.155)	-	-0.193 (0.423)	-2.714 (0.996)	-0.305 (0.380)	2.000 (0.999)	11.184 (0.671)	2.522 (0.999)	11.843 (0.618)	Cannot reject H_o	I(1)
Trade opening	-1.178 (0.078)	**-1.857 (0.031)**	**-**	**-6.9205 (0.000)**	**-3.792 (0.000)**	-1.310 (0.093)	**37.369 (0.000)**	17.867 (0.213)	**30.472 (0.006)**	18.194 (0.198)	Reject H_o	I(0)
Relative temp.	**-7.425 (0.000)**	**-5.859 (0.000)**	**-**	**-3.642 (0.000)**	**-7.224 (0.000)**	**-6.695 (0.000)**	**65.311 (0.000)**	**60.688 (0.000)**	**65.618 (0.000)**	**60.594 (0.000)**	Reject H_o	I(0)
FDI	-0.022 (0.508)	**-3.208 (0.000)**	**-**	**-3.178 (0.000)**	-1.981 (0.974)	-2.077 (0.0319)	3.311 (0.998)	**25.279 (0.000)**	2.992 (0.999)	**53.838 (0.000)**	Cannot reject H_o	I(1)
Saudi students overseas	-1.453 (0.927)	-1.855 (0.968)	-	-0.524 (0.300)	-1.540 (0.938)	-2.200 (0.986)	4.142 (0.994)	3.566 (0.997)	0.5062 (0.996)	0.473 (0.987)	Cannot reject H_o	I(1)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

Table 5.25. Panel unit root tests for variables on first differences of the variables for aggregate tourism demand from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran& Shin (IPS) W-stat**		**ADF - Fisher Chi-Sq**		**PP - Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend	individual intercept	individual intercept & trend		
The number of tourists	**-10.423 (0.000)**	**-11.949 (0.000)**	-	**-10.409 (0.000)**	**-9.167 (0.000)**	**-10.486 (0.000)**	**85.276 (0.000)**	**105.651 (0.000)**	**147.597 (0.000)**	**239.216 (0.000)**	Reject H_o	I(0)
Origin Income	**-5.791 (0.000)**	**-6.404 (0.000)**	-	-0.447 (0.672)	**-3.110 (0.000)**	**-4.981 (0.000)**	**42.021 (0.000)**	**53.511 (0.000)**	**53.274 (0.000)**	**61.509 (0.000)**	Reject H_o	I(0)
Cost of living at destination	**-3.970 (0.000)**	**-4.897 (0.000)**	-	-0.976 (0.164)	**-3.340 (0.000)**	**-3.626 (0.000)**	**34.153 (0.002)**	**37.163 (0.000)**	**39.335 (0.000)**	**46.197 (0.000)**	Reject H_o	I(0)
Cost of travel	**-7.674 (0.000)**	**-7.698 (0.000)**	-	**-4.282 (0.000)**	**-4.324 (0.000)**	**-5.364 (0.000)**	**40.549 (0.000)**	**52.222 (0.000)**	**52.296 (0.000)**	**51.621 (0.000)**	Reject H_o	I(0)
FDI	**-9.101 (0.000)**	**-10.131 (0.000)**	-	**-6.017 (0.000)**	**-4.508 (0.000)**	**-6.765 (0.000)**	**42.339 (0.000)**	**64.123 (0.000)**	**53.252 (0.000)**	**78.291 (0.000)**	Reject H_o	I(0)
Trade opening	**- 4.171 (0.000)**	**-8.759 (0.000)**	-	-0.969 (0.166)	**-5.961 (0.000)**	**-7.490 (0.000)**	**58.174 (0.000)**	**-55.978 (0.000)**	**108.547 (0.000)**	**77.990 (0.000)**	Reject H_o	I(0)
Relative temp.	**-4.983 (0.000)**	**-5.506 (0.000)**	-	**-4.166 (0.000)**	**-10.274 (0.000)**	**-10.749 (0.000)**	**96.344 (0.000)**	**98.629 (0.000)**	**142.027 (0.000)**	**126.570 (0.000)**	Reject H_o	I(0)
Students overseas	**-3.856 (0.000)**	**-4.224 (0.000)**	-	**-2.025 (0.021)**	**-4.867 (0.000)**	**-4.600 (0.000)**	**34.554 (0.001)**	**36.444 (0.000)**	**36.315 (0.000)**	**34.935 (0.001)**	Reject H_o	I(0)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

Panel data unit root tests were applied to all the variables of the model on level as well as their first differences. Panel unit root tests results are provided in Tables 5.24 and 5.25. The outcomes of the unit root tests showed that some variables were stationary I(0) on level: the number of tourists, relative temperature, and trade opening. Whereas, the income of origin countries, cost of travel, and cost of living at the destination variables in the model were non-stationary on levels, but stationary on first differences I(1). Based on these results, the cointegration relationship between the aggregate number of tourist arrivals as a dependent variable and all the independent variables could be examined. This is discussed in the next section.

5.4.4. Aggregate tourism demand cointegration test

As noted, the unit root test showed that some variables were non-stationary on their levels but were integrated (of order 1) and stationary on their first difference. Therefore, a cointegration test could be considered. Due to the panel data containing a limited number of observations, the estimation was conducted in four different specifications models. [8]

Table 5.26. Results of the panel cointegration tests for aggregate tourism demand for data from 2000 to 2019

Cointegration tests Null hypothesis: No cointegration				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Kao test ADF	Test Statistic (P-values) **-2.701** **(0.00)**	Test Statistic (P-values) **-2.841** **(0.002)**	Test Statistic (P-values) **-3.435** **(0.000)**	Test Statistic (P-values) **-1.583** **(0.005)**
Pedroni test				
H_1: Common AR coefficients (within dimension)				
Statistic				
	Test Statistic (P-values)	Test Statistic (P-values)	Test Statistic (P-values)	Test Statistic (P-values)
Panel v	-1.410 (0.920)	-3.009 (0.998)	-2.313 (0.989)	-1.442 (0.925)
Panel rho	2.215 (0.986)	2.438 (0.992)	2.587 (0.995)	1.316 (0.905)
Panel PP	**-5.624** **(0.000)**	**-5.308** **(0.000)**	**-3.612** **(0.000)**	**-5.687** **(0.000)**
Panel ADF	**-2.228** **(0.012)**	**-4.723** **(0.000)**	**-3.692** **(0.000)**	**-5.515** **(0.000)**
Weighted				

[8] The first specification model shown in column 2 includes economic factors: per capita GDP of both the origin and destination countries, cost of travel, cost of living at the destination FDI, trade openness and capital investment in the tourism sector; the second specification model shown in column 3 includes the per capita GDP of both the origin and destination countries, cost of travel, human rights, and political risks; the third specification model shown in column 4 includes the per capita GDP of both the origin and destination countries, cost of travel, global health risks, relative temperature, and Saudi students studying overseas; the fourth specification model shown in column 5 includes the per capita GDP of the origin country, the per capita GDP of Saudi Arabia, the cost of travel, and the destination prosperity index.

Panel v	-2.759 (0.991)	-3.432 (0.999)	-2.809 (0.997)	-1.834 (0.966)
Panel rho	2.628 (0.995)	2.729 (0.996)	2.731 (0.996)	1.320 (0.906)
Panel PP	**-5.586 (0.000)**	**-5.722 (0.000)**	**-4.863 (0.000)**	**-5.467 (0.000)**
Panel ADF	**-2.751 (0.000)**	**-4.562 (0.000)**	**-3.787 (0.000)**	**-6.303 (0.000)**
H_1: Individual AR coefficients (between dimension)				
Group rho	-2.759 (0.971)	3.254 (0.994)	3.428 (0.997)	2.229 (0.970)
Group PP	**-9.100 (0.000)**	**-6.966 (0.000)**	**-7.026 (0.000)**	**-6.372 (0.000)**
Group ADF	**-2.759 (0.002)**	**-4.347 (0.000)**	**-3.509 (0.000)**	**-7.056 (0.000)**

Source: Author's own calculations using EViews. P-values are shown in parentheses. **Bold** denotes that the test indicates cointegration at 5%.

The results of the cointegration tests, shown in Table 5.26, indicate that any combination of these variables was cointegrated, and the null hypothesis of no cointegration at the 1 percent level of significance was rejected. This provides support for the estimation of the model as an ARDL.

5.5.5. Empirical results and discussion of aggregate tourism demand models

5.5.5.1 ARDL model estimation

In previous section, the results of Cointegration test confirmed that any combination of independent variables with dependent variable are cointegrated, that providing support for the estimation of the model as an ARDL model. Therefore, this section presents the results of the ARDL estimator for aggregate tourism demand in Saudi Arabia.

The variables in aggregate tourism demand are cointegrated and thus they can proceed with estimating using the ARDL model. Dynamic model optimal lag length is selected based on the AIC model criterion which was taken as 1. It is worth mentioning that variables were mostly consistent in effect and significance, with different specifications.

Table 5.27. Results of panel ARDL for aggregate tourism demand from 2000 to 2019

Long-run coefficients-				
	Model 1	**Model 2**	**Model 3**	**Model 4**
Variable	Coefficient Prob.*	Coefficient Prob.*	Coefficient Prob.*	Coefficient Prob.*
Cost of travel CT_{IJ}	-0.946*** (0.000)	-0.109** (0.066)	-1.203*** (0.000)	-0.081*** (0.000)
Cost of living at destination P_{IJ}	-0.663*** (0.000)	-	-	-
Saudi income ID_J	2.762*** (0.000)	2.586*** (0.000)	2.215*** (0.000)	1.202*** (0.000)
Origin income IO_I	1.441*** (0.000)	0.551*** (0.021)	0.541*** (0.020)	0.683*** (0.000)
Trade openness	0.164	-	-	-

TADE$_{JI}$	(0.279)			
Capital investment $\boldsymbol{INVEST_J}$	2.098*** (0.000)	-	-	-
FDI $\boldsymbol{FDI_{JI}}$	0.045*** (0.000)	-	-	-
Non-economic factors				
Prosperity index $\boldsymbol{PI_J}$	-	-	-	0.008*** (0.000)
Global health risks $\boldsymbol{HR_J}$	-	-	-0.069** (0.079)	-
Political risks **PRISK$_J$**	-	-2.463*** (0.000)		-
Relative temp. $\boldsymbol{TEM_{JI}}$	-	-	0.424** (0.069)	-
Human rights index $\boldsymbol{HI_J}$	-	0.816*** (0.000)	-	-
Saudi students overseas **OVESTU$_J$**	-	-	0.991*** (0.000)	-
Short-run coefficients				
$\boldsymbol{ECT_{t-1}}$	-0.537 (0.014)	-0.579 (0.000)	-0.466 (0.000)	-0.670 (0.000)
D (cost of travel)	-0.789** (0.023)	-0.137 (0.206)	-0.354*** (0.000)	-0.098 (0.575)
D (cost of living at destination)	-0.489 (0.601)	-	-	-
D (GDP per capita in Saudi)	1.075 (0.359)	-0.294 (0.799)	-0.450 (0.686)	2.143** (0.023)
D (GDP per capita in origin countries)	0.169 (0.809)	0.738*** (0.011)	1.043*** (0.000)	0.058 (0.987)
D (Human rights)	-	0.248*** (0.011)	-	-
D (capital investment	1.079*** (0.000)	-	-	-
D (prosperity)	-	-	-	0.002 (0.857)
D (political risks)	-	-0.307* (0.074)	-	-
D (global health risks)	-	-	0.007 (0.744)	-
D (relative temp.)	-	-	1.063 (0.683)	-
D (trade openness)	0.364 (0.367)	-	-	-
D (FDI)	0.036 (0.184)	-	-	-
D (Saudi students overseas)	-	-	0.392*** (0.037)	-
Constant	-11.553 (0.019)	-24.119 (0.000)	-50.028 (0.000)	11.789 (0.000)

Source: Author's own calculations using EViews. *Notes:* *** 1% significant, **5% significant and * 10% significant. Model selection method: Akaike info criterion (AIC).

The empirical results for the aggregate tourism demand model are presented in Table 5.27. In the estimated models, all explanatory variables were significant either at a 1 percent or 5 percent significance level in the long run. The exception was trade openness between Saudi Arabia and the origin nations, being insignificant in the estimated models. In the short-term equation, the error correction coefficient of the cointegration equation had a negative sign -0.537, -0.579, -0.466 and -0.670 for the four models and was significant. This means that the variables converge to the long-run equilibrium, and the convergence rate is 53 percent, 57 percent, 46 percent and 67 percent. The income of the destination, political risks, and capital investment in the tourism sector at the destination were the most influential factors for international tourism demand to Saudi Arabia.

Economic factors

The income levels of the origin countries and destination country positively affect tourism demand in Saudi Arabia and , a 1 percent increase in income in the origin countries lead to increase in tourist arrivals by 1.44, 0.55,0.54 and 0.68 percent respectively (on average 0.80) ceteris paribus and a 1 percent increase in income in destination country, lead to increase in tourist arrivals by 2.76, 2.58 ,2.21 and 1.20 percent respectively(on average a 2.19), ceteris paribus. The positive effects of the GDP of destination and origin countries has also been empirically validated by Ghalia et al. (2019), Hanafiah and Harun (2010), Lim (1997a), Martins et al. (2017), and Rosselló et al. (2020).

The cost of living at the destination variable was significant with the expected negative sign. As the estimated coefficient of price in this model was less than one, tourism demand in Saudi Arabia is price inelastic. This result is consistent with prior empirical research findings. For example, Naudé and Saayman (2005), and Surugiu et al. (2011) claimed that demand for international tourism to developing economies is less sensitive to price variations. As a result, lower elasticity is predicted. According to the estimated model, a 1 percent increase in price leads to a 0.663 percent decrease in tourist arrivals, ceteris paribus. This result supports previous studies by Eilat and Einav (2004), Görmüş and Göçer (2010), Habibi (2017), Rosselló-Nadal and HE (2019), Tang (2018), and Xu et al. (2019), who found a negative significant relationship between price and international tourism demand.

Transport cost was significant in all the estimated models with a negative sign in the long and short run (models 1 and 3). The elasticity in the estimated models ranged from -0.081 to -1.203. A 1 percent increase in transport cost led to a -0.584 percent increase in tourist arrivals in Saudi Arabia, ceteris paribus. This supports the findings of previous studies, including Aki (1998), Chaiboonsri et al. (2010), Chaitip and Chaiboonsri (2009), Kaplan and Aktas (2016), and Khadaroo and Seetanah (2008).

The regression results demonstrate that trade openness did not have a significant impact on tourism but with the correct sign. Numerous studies have provided empirical evidence in support of the positive impact of trade openness on tourism demand, including Adeola et al. (2018), and Asrin et al. (2015). Moreover, tourism-related investment in Saudi Arabia has a positive impact on tourism demand. A 1 percent increase in tourism investment would increase tourism demand by 2.098 percent in the long run and 1.07 percent in the short run, other factors being held constant. This indicates that investment is an important factor for driving tourism development in Saudi Arabia, leading to more tourism demand. This result is in line with the work of several scholars, including Adeola et al. (2018), Jeje (2021), Naudé and Saayman (2005), and Nonthapot (2017), who argued that capital investment in the tourism sector leads to an increase in international tourist arrivals.

The regression results demonstrate that FDI was a significant driver for the decision to travel to Saudi Arabia. The relationship between tourism at an aggregated level and FDI in Saudi Arabia over the period 2000 to 2013 was examined by Alam et al. (2016b). Their findings indicated that there is a positive relationship between tourism receipt and the number of tourists with FDI in the short-term and long-term relationship, and there is a bidirectional causality running between tourism expenditure and FDI. Additionally, this result confirms the findings of Adeola et al. (2018), Asrin et al. (2015), and Osinubi et al. (2022), which showed FDI has a positive and significant impact on tourism demand.

Non-economic factors

The effect of the political risk variable was significant with a negative sign, as expected. Based on the model estimation, a one-unit increase in the political risk index decreased tourist arrivals in Saudi Arabia by 2.463 in the long run and 0.30 in the short run, ceteris paribus. This means political stability in a destination country is a crucial factor in attracting international tourism flows. This finding is consistent with the work of Ghaderi et al. (2017), Llorca-Vivero (2008), Saha et al. (2017), Saha and Yap (2014), and Yap and Saha (2013), who found that political instability had a significant negative impact on tourism demand.

Relative temperature had a positive and significant impact on tourism demand. A 1 percent increase in ratio temperature would increase tourism demand by 0.424 percent, other things being held constant. This positive relationship means that the greater the ratio of the origin country temperature to destination country temperature, the higher the tourism demand in Saudi Arabia from the tourist's source market. This result is consistent with the work of Li et al. (2017), who found that temperature has a positive effect on tourism demand.

In this study, estimated coefficients of global health risks had a negative and significant effect on tourism demand. The evidence of a negative impact of global health risks on tourist flow is consistent with the results reported in several studies (Karabulut et al., 2020; Rosselló et al., 2017; Uzuner & Ghosh, 2020). For example, Karabulut et al. (2020) found that the impact of pandemics on tourist arrivals was minimal in advanced and emerging economies, but more pronounced in low-income countries. In low-income economies, a lack of transparency and healthcare infrastructure may be the primary reasons for declining tourism demand.

The results of the current study indicate that human rights development positively impacts tourism demand in Saudi Arabia. In this context, Neumayer (2004) argued that there is a negative correlation between human rights violations, conflict, and other politically driven violent events and the number of tourists visiting a country. Moreover, as expected, Saudi Arabian students studying overseas were positively related to VFR tourism. The estimated number of Saudi international students' elasticity was 0.991 percent. Saudi students studying overseas have contributed to total tourism demand.

This study found that the relationship between the destination prosperity variable and total number of tourists to Saudi Arabia was positive and significant (see Table 5.27). This means destination prosperity plays a significant role in determining tourist arrivals to Saudi Arabia.

5.5.5.2 Panel regression model estimates

As mentioned earlier, due to uncertainties over the validity of unit root and cointegration tests in small samples, panel regression model estimates were conducted in this study. This was undertaken to investigate the factors that influence the aggregate tourism demand by assuming that all variables are stationary. The Chow test, Lagrange multiplier tests and Hausman test indicted that FE was the most appropriate model. The FE estimation result is provided in Table 5.28.

Table 5.28. Estimation results of FE and RE tourism demand from 2000 to 2019

The results of FE and RE		
	FE model	**RE model**
Variable	Coefficient Prob.*	Coefficient Prob.*
Cost of travel **CT_{ij}**	-0.095*** (0.035)	-0..065** (0.064)
Cost of living at destination $\boldsymbol{P_{IJ}}$	-0.003*** (0.008)	-0.071 (0.200)
Saudi income $\boldsymbol{ID_J}$	2.613*** (0.000)	2.013*** (0.000)
Origin income $\boldsymbol{IO_I}$	0.312** (0.003)	0.021*** (0.000)
Capital investment $\boldsymbol{INVEST_J}$	0.305*** (0.000)	0.323** (0.016)
Trade openness **$TADE_{JI}$**	0.461** (0.050)	0.252** (0.080)
FDI $\boldsymbol{FDI_{JI}}$	0.117*** (0.021)	0.115*** (0.000)
Non-economic factors		
Prosperity index $\boldsymbol{PI_J}$	1.022** (0.055)	1.122*** (0.004)
Global health risks $\boldsymbol{HR_J}$	-0.014 (0.148)	-0.003 (0.897)
Political risks **$PRISK_J$**	-1.092*** (0.006)	-2.037*** (0.000)

Relative temp. TEM_{JI}	0.917* (0.094)	0.412 (0.816)
Human rights index HI_J	0.044*** (0.015)	0.293*** (0.009)
Saudi students overseas $\mathbf{OVESTU}_J$	0.183** (0.052)	0.120*** (0.000)
Language	-	-0.232 (0.623)
Religion	-	0.398 (0.629)
Visa restrictions	-	-1.063*** (0.000)
R-squared	0.82	0.49
Adjusted R-squared	0.79	0.48
F-statistic **Prob (F-statistic)**	15.464 (0.000)	72.012 (0.000)

Note: *** 1% significant, **5% significant and * 10% significant

In general, the results of the FE estimation were consistent with the panel ARDL model results, except that trade openness had a positive and statistically significant impact on aggregate tourism demand, but it was not significant in the ARDL model. The FE panel goodness of fit test R^2 was high, indicating that the estimated predictors explained 82 percent of the variation in total international tourism arrivals to Saudi Arabia. The p-value of the models (Prob >F=0.000) was statistically significant, which means that the estimated predictors reliably predicted international tourism arrivals to Saudi Arabia.

Shared religion and language between destination and origin countries were not important factors to explain total tourism demand to Saudi Arabia. Visa restrictions had a large negative effect on tourist flows to Saudi Arabia. These restrictions are likely to deter visitors from certain countries. This result aligns with the findings of past studies, such as Özdemir and Tosun (2022).

5.6. Comparison of the long-run impacts on religious, business, VFR, and total tourism demand

This section compares economic and non-economic factors across total, religious, business, and VFR tourism to determine the long-run impact of these factors and how they vary according to purpose of visit.

The primary reason for the estimate of disaggregate models is that different types of tourists can respond differently to economic and non-economic factors. In contrast to an aggregate model, therefore, disaggregate analysis could provide additional insight into the nature of the effects of various factors on tourism demand. Although modelling tourism demand is a crucial aspect of tourism policy, the literature is dominated by aggregate models due to the difficulties of obtaining disaggregate data. The disaggregated analysis performed in this study has revealed several significant findings. Table 5.29

shows the long-run significant impacts of factors on total, religious, business, and VFR tourism demand from 2000 to 2019.

Table 5.29. Comparison of long-run significant impacts on religious, business and VFR tourism

Variable	Religious	Business[9]	VFR	Aggregate
Word-of-mouth	0.829***	-	-	-
Income of origin country	0.671***	0.832***	0.959***	0.804***
Saudi income	2.417***	0.707***	1.556***	2.191***
Cost of living at destination (tourism price)	-1.058***	-0.261***	-0.178	-0.663***
Cost of travel	-0.486***	-0.886***	-0.744***	-0.584***
Capital investment	0.055***	0.440***	1.616***	2.098***
Trade openness	-	1.403***	-	0.164
FDI	-	0.012	-	0.045***
Human rights	0.419**	1.128***	0.315	0.816***
Political risk	-1.599***	-0.748***	-0.372***	-2.643***
Global health risks	-0.017	-0.119***	-0.036	-0.069**
Prosperity	0.037**	0.294***	0.553**	0.008***
Relative temp.	-0.466***	-1.117	0.186	0.424**
Saudi students overseas	-	-	0.369***	0.992***
Visa restrictions	-0.51***	-	-1.177***	-1.063***
Language	-0.532***	-0.085	0.072	-0.232
Religion	1.055	-0.490	0.0466	0.398

Source: Author's own calculations using EViews. *Note:* *** 1% significant, ** 5% significant and * 10% significant.

5.6.1. Economic factors

The impact of origin country income was positive and significant in all types of tourism demand. This is consistent with the theoretical prediction that increases in tourist income in the origin country will lead to an increase in the ability to travel. When making comparisons, it was observed that VFR and aggregate tourism demand are more sensitive to changes in origin country income, whereas religious and business tourism demand was less sensitive to this variable. It is clear that the magnitude of the income effect on the demand for international tourism is less when the demand is for a particular 'product' (e.g., Hajj and Umrah), as can be seen in religious tourism. For business tourists, companies may cover the cost of travel, in part or in full (Senadeerage, 2020). However, VFR tourism is more flexible because determined by the individual traveller than religious and business tourism and, therefore, is more likely to be impacted by income.

In this study, since the elasticity of the average income of tourists was less than 1, this implied that international travel to Saudi Arabia was more of a necessity than a luxury. This evidence is important because it implies that, whilst an increase in tourist income does not result in a greater than proportional increase in demand, a decrease in income will have a lesser impact on the destination. These findings

[9] The visa restrictions variable was not estimated in the business and aggregated models because their samples did not include countries without restrictions (except Kuwait in business tourism demand).

align with those of Gozgor et al. (2021), who found that tourist income is an important factor that impacts on VFR tourism demand but is not significant for business purposes and the elasticity of tourist income is less than 1. Naudé and Saayman (2005) demonstrated that the level of affluence in origin nations has little impact on tourism demand in Africa. This is contrary to previous research on tourism demand, which found that income elasticities are greater than one and that international tourism demand is a luxury good. For example, Croes and Vanegas Sr (2005) found that the estimated income elasticity of demand for Aruba tourism ranged from 1.43 for American tourists, to 2.50 for Dutch visitors. Cortés-Jiménez and Blake (2011) showed that the income elasticity of demand for holiday tourism ranged from 1.37 to 2.10.

The estimation results in this study show that destination country income was an important determinant for explaining Saudi Arabia's tourism demand for all models and was more important for religious tourism demand. This finding indicates that a destination with a high income can provide essential services, including infrastructure, health care, transportation, accommodation, and entertainment facilities. This leads to increasing demand for visits to Saudi Arabia. Increased destination income means the country can afford to meet tourist requirements. For religious tourism, in addition to the expansion projects in holy cities such as the construction of roads, tunnels, and bridges, the kingdom spends significant funds on care services for pilgrims (e.g., providing security, services to ensure well-being and hygiene, as well as facilitating movement, especially for those with special needs, and the elderly). This requires a strong economy capable of meeting these requirements.

The cost of living at the destination (tourism price) variable had a significant and adverse impact on all types of tourism demand except for VFR tourism, which had a negative but insignificant impact. This might be because VFR tourists stay with their friends and relatives, making the cost of living in the destination less important (Zentveld & Yousuf, 2022). The destination cost of living was more important to religious tourism demand. This may be because accommodation, transportation, and living costs increase significantly during seasons such as Hajj and Ramadan (Karimah & Iskandar, 2020; Robin, 2022). Ladki and Mazeh (2017), and Usman (2016) stated that higher Hajj prices for lower middle income and moderate economies make the pilgrimage too expensive and out of reach for some potential pilgrims.

The cost of travel negatively impacted all types of tourism demand under investigation in this study. Business tourism demand showed more sensitivity to travel costs, while religious tourism was less sensitive. This may due to the fact that the majority of business passengers must travel during peak times, which are associated with higher costs and the pricing strategies of air transport companies, plus some business travellers pay for their own trips (Camilleri, 2018). It may also be due to the fact that the origin countries sampled in this study are developing counties and their economies may impact their citizens' ability to afford the cost of business travel.

Trade openness had a positive and significant impact only on business tourism demand. A destination country's openness to trade requires business trips to maintain the international trade of goods (Khan & Upadhayaya, 2019; Kulendran & Wilson, 2000a). Trade openness had a positive and insignificant impact on the aggregate number of tourists in the ARDL model but is was significant in the FE models. Countries that have a trade relationship with Saudi Arabia are associated with business tourism demand.

FDI was a significant factor only on the determination of total tourism demand. FDI did not significantly impact business travel, which might be due to a number of reasons. Developing nations have minimal FDI in the tourism sector because they use FDI to address other economic difficulties. Economic environments in resource-rich countries that exploit, and export natural resources have a regular cash stream and therefore do not need external finances to fund expansion. Furthermore, some of these countries are concerned that FDI will compete with existing local investments (Haque, 2021). Previous studies, such as Selvanathan et al. (2012), and Tang et al. (2007), have found that FDI plays a significant role in increasing tourism demand. They found a positive and significant relationship between FDI and tourist arrivals. Countries with liberalisation and deregulation policies have attracted a considerable amount of FDI and FDI can drive the country's overall development, including the tourism sector. In contrast, a few studies have found FDI has a negative impact on tourism demand, such as Munir and Iftikhar (2021). Moreover, Siddiqui and Siddiqui (2019) found no relationship between FDI and tourism.

Capital investment in the tourism sector had a positive statistically significant effect on all types of tourism demand. Capital investment in tourism in destination countries increases government revenue, creates employment opportunities, promotes tourism infrastructure, and, as a result, increases tourist numbers. Therefore, capital investment in tourism in Saudi Arabia is a very important factor for explaining total international tourism demand and VFR tourism demand. VFR tourists often spend a longer time in a destination than non-VFR travellers. VFR tourists also participate in various activities and use different facilities and infrastructure (Kashiwagi et al., 2020). Capital investments in travel and tourism have a considerable impact on the creation of attractive destinations and the management of the efficient supply of tourism services. Investments can be translated into the development of appropriate tourist accommodation and restaurant or catering services, the creation of affordable and reliable transport services and improved tour guide operations, as well as other investments that aim to support the tourism industry, such as the establishment of ICT, logistics, finance, and marketing companies. In addition to contributing to enhancing the attractions of destinations, these investments are the primary source of employment opportunities. Investors in the tourism sector have a responsibility to invest in the competency and welfare of their staff. Human resources play a crucial role in developing the tourism industry (Jeje, 2021). Investments in human resources lead to increased competitiveness within the tourist industry, and an associated increase in tourist numbers. Nonthapot (2017) revealed bidirectional long-run causality between capital investment in the tourism sector and inbound tourist arrivals.

5.6.2. Non-economic factors

The estimated coefficients of word-of-mouth were positive and statistically significant on religious tourism demand. The human rights index was positively related to the total number of tourist arrivals, religious, business, and VFR tourist arrivals to Saudi Arabia, with the range of elasticity at 0.81, 0.41, 1.1 and 0.31, respectively. Business tourism demand to Saudi Arabia was very sensitive to the development level of respect for human rights in the destination country. This is known as the image effect. The development of human rights can be seen as signalling a shift to a more democratic regime. In turn, this can improve the image of a country worldwide, creating a more positive reputation and thus encouraging tourists. Oreja-Rodríguez and Yanes-Estévez (2007) argued that geographical, political-legal, social, and economic factors all play a role in determining and influencing business managers' perspectives on investing in other countries.

Political risk had a negative impact on all types of tourism demand. This implies that a peaceful environment is essential to the growth of the country's tourism industry. Religious tourism was observed as more sensitive to political risk, perhaps because of the risks associated with the gathering of a large number of pilgrims in one place (Bahurmoz, 2006).

The Saudi students' overseas factor had a positive and statistically significant effect on both aggregate and VFR tourism demand. This may be because Saudi Arabian students studying abroad return to visit their family and friends during study periods. Saudi Arabian students and their families are given free round-trip airline tickets every year to visit their families, funded by Saudi KASP. As part of this scholarship program, thousands of Saudi Arabian students have travelled abroad to pursue undergraduate and graduate degrees. Approximately 9,000 Saudi students were funded by KASP in 2006 to study overseas, and by 2012 that number had climbed to 140,000 (Alsulami, 2016). Ministry of Finance statistics from 2014 show that there were 185,000 Saudi students (undergraduate and graduate) studying in 23 different countries.

Destination prosperity was identified as a significant factor to explain total, religious, business, and VFR tourism demand. However, VFR tourism demand was more sensitive to this variable. As previously explained in relation to the capital investment variable, VFR tourists often spend more time in the destination, and they benefit from the services and the quality of life in that destination.

Relative temperature had different impacts according to the purpose of visit. It had a negative and significant impact on religious and aggregate tourism, but was not significant in business and VFR tourism demand. Its importance for religious tourism may relate to the fact that Hajj occurs during the summer months, when Saudi Arabia is quite hot. Extreme weather and heat waves could become a major cause of illness or death among pilgrims if essential precautions are not taken (e.g., reducing their activity levels and consuming more water) (Yezli, 2021).

Restrictions on travel visas to Saudi Arabia discouraged tourists for the purposes of religion, VFR and impacted the total number of tourists. VFR tourists were more sensitive to visa restrictions than religious tourists. That may be because there are some barriers to obtaining a visitor visa (Ekiz et al., 2017). In the past, visitor visas could not be approved during religious activities such as Ramadan and Hajj. It was also restricted to immediate family members only (i.e., parents, siblings, spouses, and children), not extended family members (VisaGuide, n.d.).

Global health risks negatively impacted all types of tourism demand under investigation in this study, but it was a more important factor for business and aggregate tourism demand. Smeral (2010) suggested that crises typically affect business travel more seriously than leisure travel. That may because business travel depends on economic stability, market opportunities, and business potential. Thus, pandemics and restrictions have made it harder to keep and grow a business and, in some cases, have led to economic recession (Olkiewicz, 2022). This has had a significant and negative impact on inbound business travel.

Shared religion between the destination and origin countries was observed to be a robust factor for explaining religious tourism demand. However, shared language and religion were not key motivators for tourists travelling to Saudi Arabia for business and VFR purposes.

As mentioned previously, the magnitude and direction of the effects of economic and non-economic variables on different categories of demand vary considerably. Therefore, this research reflects two crucial factors for tourism demand researchers. First, researchers must identify which economic and non-economic factors impact all types of tourism demand. Second, researchers should investigate whether the impact of economic and non-economic factors varies according to the purpose of the visit.

5.7. Models of tourism demand for expatriate workers

Saudi Arabia has employed a large number of expatriate workers, accounting for more than 83% of private-sector jobs (Ishac, 2016). In 2019, about 38.3 percent of Saudi Arabia's total population was made up of expatriate workers (CIA, 2019). Saudi Arabia is the second largest destination for migrant workers in terms of population percentage (Ahmed et al., 2020). In the tourism demand context, the number of immigrants (expatriate workers) is important, as the larger the number of immigrants from a particular country, the greater the number of friends and relatives who have the incentive to visit the destination country.

A large number of expatriate workers also means less money spent on accommodation because visitors have places to stay. Backer (2010), and Janta et al. (2015) emphasised that tourists frequently depend on their friends and family in the destination as their primary source of information, through which they gain access to tourist and non-tourist attractions. Several studies have examined the effect of immigration on the economy of the host country and have revealed additional pathways via which immigration can increase tourist arrivals (Dwyer, 2002; Massidda et al., 2015; Seetaram, 2012). This includes the fact that immigrants can act as commercial mediators and reduce market information asymmetries. Immigrants usually have an exceptional level of knowledge of the products, marketplaces, distribution networks, and both formal and informal institutional contexts of both their country of origin and their place of residence. Immigrants usually have language skills that enhance the creation and expansion of import and export firms (Combes et al., 2005; Iranzo & Peri, 2009).

Consequently, there are positive effects on tourism and other industries as a result of immigrants using their knowledge and skills to reduce informational frictions and trade barriers. Bilateral tourism flows, including business and VFR travellers, tend to rise as a consequence of immigrants' capacity to boost demand for goods from their home countries (Felbermayr & Toubal, 2012; Seetaram, 2012). Additionally, immigrants can boost a country's reputation in the tourism sector of their country of origin. Although research on migration and tourism has been investigated, the specific relationship between expatriate workers and tourism has been neglected. The presence of migrant workers in Saudi Arabia may also assist their family and friends to come for Umrah and Hajj, providing them with information about the required procedures and applications.

The main aim of this section is to investigate the impact of expatriate workers in the destination country on Saudi Arabia's inbound tourism in order to assess the pulling forces to the destination. In particular, this section focuses on whether or not expatriate workers affect religious, business and VFR tourism demand. To this end, since the data on expatriate workers is only available for eight countries, this study estimated the models separately from religious, business, and VFR tourism demand. To estimate expatriate worker tourism demand, this study used the ARDL model as the number of origin countries is eight and the time series is 20 (N >T).

Section 5.7.1 presents the descriptive statistics of the data; Section 5.7.2 discusses the correlation matrix of all the variables and Section 5.7.3 outlines the unit root tests. Finally, Section 5.7.4 discusses the estimation approach and empirical results.

5.7.1. Descriptive statistics for expatriate worker models

Table 5.30 summarises the descriptive statistics, including the mean, median and standard deviation of all variables used in the empirical analysis from 2000 to 2019. The dependent variable is the number of religious, business and VFR tourists, and the four independent variables are cost of travel, Saudi income, origin country income and expatriate workers.

Table 5.30. Descriptive statistics for expatriate worker models from 2000 to 2019

	Number of religious tourists	Number of business tourists	Number of VFR tourists	Cost of travel	Per capita GDP of Saudi	Per capita GDP origin	Expatriate workers
Mean	426,298	92,819	53,025	177,140	19,694	2,209	642,294
Median	306,821	51,507	32,000	172,604	19,607	1,797	594,613
Maximum	1,925,085	910,587	542,156	306,234	21,399	5,931	2,266,216
Minimum	9,521	2,000	7,233	67,033	16,696	525	4,865
Standard deviation	398,531	138,327	65,185	78,210	1,306	1,370	521,068

Table 5.30 shows that the average number of tourists arriving in Saudi Arabia for religious, business and VFR purposes over the study period were approximately 426,298, 92,819, and 53,025 respectively. This demonstrates the significant variation in the number of tourists visiting Saudi Arabia from different nations. In addition, there was a high degree of variability in transport costs, which could be attributed to the fluctuation in oil prices. The total average number of expatriate workers in Saudi Arabia throughout the study period was approximately 642,294, ranging from 4,865 to 2,266,216. This significant degree of variability is 1.678047 and may reflect the number of expatriate workers in Saudi Arabia from countries that differ from those in our other samples. The largest expatriate communities in Saudi Arabia come from Bangladesh, India, Indonesia, and Pakistan, followed by Egypt, Jordan, Iraq, and Sudan.

5.7.2. Expatriate worker models correlation matrix

This section presents the matrix showing the correlation between independent variables. Multicollinearity among the independent variables was checked. The values were all below 0.70 (see Table 5.31), suggesting the absence of a multicollinearity problem.

Table 5.31. A Pearson correlation matrix between explanatory variables for expatriate worker models from 2000 to 2019

Religious tourism pairwise correlation matrix Pearson correlation matrix between explanatory variables				
Variables	**Cost of travel**	**Expatriate workers**	**Per capita GDP of Saudi**	**Per capita GDP of origin countries**
Cost of travel	1.000			
Expatriate workers	0.296	1.000		
Per capita GDP of Saudi	0.329	0.498	1.000	
Per capita GDP of origin countries	0.087	0.654	0.330	1.000
Business tourism pairwise correlation matrix Pearson correlation matrix between explanatory variables				
	Cost of travel	**Per capita GDP of Saudi**	**Expatriate workers**	**Per capita GDP origin**
Cost of travel	1.000			
Per capita GDP of Saudi	0.055	1.000		
Expatriate workers	0.473	0.353	1.000	
Per capita GDP origin countries	-0.495	0.276	-0.260	1.000
VFR tourism pairwise correlation matrix Pearson correlation matrix between explanatory variables				
	Cost of travel	**Per capita GDP of Saudi**	**Expatriate workers**	**Per capita GDP origin countries**
Cost of travel	1.000			
Per capita GDP of Saudi	0.061	1.000		
Expatriate workers	0.247	-0.572	1.000	
Per capita GDP origin countries	0.415	0.132	0.348	1.000

Source: Author's own calculations using EViews.

5.7.3. Expatriate worker unit root tests

The previous section outlined the testing of multicollinearity among explanatory variables using a pairwise correlation matrix. This section presents the test results for the stationarity of the variables that were used in these models before regression analysis was carried out.

To test for unit roots or stationarity, this study used a variety of tests in panel datasets: the LLC test, the Breitung test, IPS test, the Fisher-ADF test, and the PP – Fisher Chi-square. The null hypothesis was that all the panels contain a unit root. The panel unit root tests were conducted on the levels and first differences of the variables.

Table 5.32. Panel unit root tests for expatriate worker panel models on level from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		**Breitung t-stat**		**Im, Pesaran and Shin (IPS) W-stat**		**ADF - Fisher Chi-Sq**		**PP - Fisher Chi-Sq**		**Decision**	**Order of integration**
Variables	individual intercept	individual \ intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend		
Number of religious tourists	**-1.590 (0.055)**	**-4.1260 (0.000)**	-	**2.400 (0.008)**	**-2.835 (0.002)**	**-2.550 (0.005)**	20.173 (0.189)	**35.422 (0.003)**	19.929 (0.223)	59.141 (0.000)	Reject H_o	I(0)
Number of business tourists	**-3.603 (0.000)**	**-4.201 (0.000)**	-	-0.128 (0.445)	**-2.406 (0.008)**	**-1.745 (0.040)**	**32.500 (0.008)**	**26.624 (0.045)**	**31.738 (0.010)**	**40.773 (0.000)**	Reject H_o	I(0)
Number of VFR tourists	**-4.993 (0.000)**	**-4.247 (0.000)**	-	**-4.414 (0.000)**	**-4.913 (0.000)**	**-2.656 (0.003)**	**55.421 (0.000)**	**40.590 (0.000)**	**51.353 (0.000)**	**37.882 (0.001)**	Reject H_o	I(0)
Cost of travel	-1.486 (0.935)	-0.255 (0.399)	-	-0.311 (0.37)	-2.759 (0.997)	-1.0254 (0.847)	2.601 (0.999)	7.218 (0.968)	3.043 (0.999)	3.043 (0.999)	Cannot reject H_o	I(1)
Per capita GDP of Saudi	-2.129 (0.983)	-2.115 (0.017)	-	-0.161 (0.435)	-3.291 (0.995)	0.4353 (0.668)	1.789 (0.998)	8.963 (0.914)	1.780 (0.999)	8.950 (0.915)	Cannot reject H_o	I(1)
Per capita GDP origin	-0.7436 (0.771)	-0.7436 (0.771)	-	-3.652 (0.999)	-2.004 (0.975)	-3.652 (0.999)	16.420 (0.424)	9.132 (0.907)	7.523 (0.961)	29.207 (0.022)	Cannot reject H_o	I(1)
Expatriate workers	**-4.462 (0.000)**	**-3.991 (0.000)**	-	**-1.548 (0.060)**	**-23.582 (0.000)**	3.0400 (0.998)	**78.419 (0.000)**	**108.255 (0.000)**	**85.396 (0.000)**	**63.380 (0.000)**	Reject H_o	I(0)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests. Figures in **bold** indicate that the variable is stationary at 5%.

Table 5.32 presents the data on the levels; Table 5.33 presents the results for the first differences. Regarding level variables, the income of Saudi Arabia, the income of origin nations, and travel cost (transportation cost) variables were non-stationary on level. However, the same tests on the first difference provided clear evidence that the variables on the first difference were stationary (0). Thus the variables on level are a mixture of I (1) and I(0), which justified the use of a panel ARDL estimation.

Table 5.33. Panel unit root tests for expatriate worker panel model on first difference from 2000 to 2019

The null hypothesis (H_0) is the panel series has a unit root												
	Levin, Lin & Chu (LLC)		Breitung t-stat		Im, Pesaran & Shin (IPS) W-stat		ADF - Fisher Chi-Sq		PP - Fisher Chi-Sq		Decision	Order of integration
Variables	individual intercept	individual\ intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend	individual intercept	individual intercept &Trend		
Number of religious tourists	**-11.933 (0.000)**	**-8.026 (0.000)**	**-**	**-9.802 (0.000)**	**-10.498 (0.000)**	**-9.802 (0.000)**	**93.756 (0.000)**	**69.616 (0.000)**	**393.411 (0.000)**	**165.391 (0.000)**	Reject H_o	I(0)
Number of business tourists	**-9.657 (0.000)**	**-12.558 (0.000)**	**-**	**-8.979 (0.000)**	**-8.985 (0.000)**	**-10.064 (0.000)**	**88.804 (0.000)**	**111.238 (0.000)**	**140.090 (0.000)**	**407.638 (0.000)**	Reject H_o	I(0)
Number of VFR tourists	**-15.766 (0.000)**	**-13.421 (0.000)**	**-**	**-7.372 (0.000)**	**-13.799 (0.000)**	**-12.143 (0.000)**	**152.555 (0.000)**	**114.244 (0.000)**	**267.681 (0.000)**	**135.393 (0.000)**	Reject H_o	I(0)
Cost of travel	**-7.767 (0.000)**	**-6.254 (0.000)**	**-**	**-3.987 (0.000)**	**-5.052 (0.000)**	**-3.987 (0.000)**	**50.367 (0.000)**	**43.476 (0.000)**	**54.735 (0.000)**	**57.798 (0.000)**	Reject H_o	I(0)
GDP per capita of Saudi	**-9.492 (0.000)**	**-9.307 (0.000)**	**-**	**-5.776 (0.000)**	**-5.897 (0.000)**	**-6.78749 0.0000**	**57.944 (0.000)**	**70.841 (0.000)**	**68.461 (0.000)**	**95.393 (0.000)**	Reject H_o	I(0)
GDP per capita of origin countries	**-7.228 (0.000)**	**-5.090 (0.000)**	**-**	**-3.499 (0.000)**	**-5.427 (0.000)**	**-4.53540 0.0000**	**54.372 (0.000)**	**58.484 (0.000)**	**66.322 (0.000)**	**75.298 (0.000)**	Reject H_o	I(0)
Expatriate workers	**-12.621 (0.000)**	**-16.590 (0.000)**	**-**	**-1.451 (0.073)**	**-31.980 (0.000)**	**-15.219 (0.000)**	**154.887 (0.000)**	**139.960 (0.000)**	**156.717 (0.000)**	**132.512 (0.000)**	Reject H_o	I(0)

Notes: All unit root tests were performed with the individual intercept and individual intercept and trend for each series. The optimal lag length was selected automatically using the Schwarz information criteria (SIC). P-values are presented in parentheses. In the case of individual intercept (in EViews), we have lost Breitung's test. The null hypothesis is a unit root for all the tests.

5.7.4. Cointegration test for the expatriate worker models.

As discussed in the previous section, the unit root test results showed that some variables were non-stationary on their levels but were integrated (of order 1) and stationary on their first difference. Therefore, a cointegration test could be considered. The results shown in Table 5.34 indicate that any combination of these variables was cointegrated, providing support for the estimation of the model as an ARDL. Having identify that the variables were I (0) and I(1), the Kao and Pedroni cointegration test was utilised in this study.

Table 5.34. Results of panel cointegration tests for data from 2000 to 2019

Cointegration tests Null hypothesis (H_0) of both panel Kao and Pedroni test is no cointegration				
	Religious	**Business**	**VFR**	**Total Arrivals**
Kao test ADF	Test Statistic (P-values) **-4.043** **(0.000)**	Test Statistic (P-values) **-2.792** **(0.002)**	Test Statistic (P-values) **-2.970** **(0.001)**	Test Statistic (P-values) **-3.535** **(0.000)**
Pedroni Test				
H_1: Common AR coefficients (within dimension)				
Statistic				
	Test Statistic (P-values)	Test Statistic (P-values)	Test Statistic (P-values)	Test Statistic (P-values)
Panel v	-0.644 (0.740)	-1.500 (0.933)	-0.306 (0.620)	-2.488 (0.993)
Panel rho	1.707 (0.956)	1.253 (0.895)	-0.445 (0.328)	1.603 (0.94)
Panel PP	**-3.395** **(0.000)**	**-4.781** **(0.000)**	**-5.576** **(0.000)**	**-4.193** **(0.000)**
Panel ADF	**-3.817** **(0.000)**	**-4.481** **(0.000)**	**-5.247** **(0.000)**	**-3.816** **(0.000)**
Weighted				
Panel v	-1.049 (0.853)	-2.284 (0.988)	-1.151 (0.875)	-4.187 (1.000)
Panel rho	1.285 (0.900)	1.170 (0.879)	-0.020 (0.491)	1.549 (0.939)
Panel PP	**-3.053** **(0.001)**	**-4.996** **(0.000)**	**-6.044** **(0.000)**	**-16.296** **(0.000)**
Panel ADF	-3.231 (0.000)	-4.914 (0.000)	-5.403 (0.000)	-13.204 (0.000)
H_1: Individual AR coefficients (between dimension)				
Group rho	2.522 (0.994)	2.563 (0.994)	1.231 (0.892)	2.450 (0.992)
Group PP	**-4.881** **(0.000)**	**-7.136** **(0.000)**	**-8.302** **(0.000)**	**-12.319** **(0.000)**
Group ADF	**-3.467** **(0.000)**	**-5.134** **(0.000)**	**-5.591** **(0.000)**	**-7.882** **(0.000)**

Source: Author's own calculations using EViews. P-values are shown in parentheses. **Bold** denotes that the test indicates cointegration at 5%.

5.7.5. Empirical results and discussion of the expatriate worker models.

As noted in the previous section, the results of the cointegration test confirmed that any combination of independent variables with the dependent variable were cointegrated, thus supporting the use of the ARDL model. This section presents the results of the ARDL estimator for the expatriate worker models for tourism in Saudi Arabia. It presents the regression results based on the panel ARDL method for the period 2000 to 2019. In order to interpret the results, the estimated coefficients were long-run and short-run demand elasticities. The variables were cointegrated and thus, estimating the long-run coefficients using the ARDL model could proceed.

The short-run dynamic model optimal lag length was selected based on the AIC model criterion, which was taken as 1. The model was estimated over aggregate and disaggregate tourism demand models (religious, business, and VFR). The results are presented in Table 5.35.

Table 5.35. Results of expatriate worker models of tourism demand

	ARDL - Religious tourism demand	FE model - Religious tourism demand	ARDL - Business tourism demand	FE model - Business tourism demand	ARDL - VFR tourism demand	FE model - VFR tourism demand	ARDL - Aggregate tourism demand	FE model - Aggregate tourism demand
Variable	**Coefficient Prob.***	**Coefficient Prob.***	**Coefficient Prob.***	**Coefficient Prob.***	**Coefficient Prob.***	**Coefficient Prob.***	**Coefficient Prob.***	**Coefficient Prob.***
	Long-run coefficients	-	**Long-run coefficients**	-	**Long-run coefficients**	-	**Long-run coefficients**	-
Origin income IO_I	0.561** (0.049)	-0.063** (0.067)	0.798*** (0.007)	0.995*** (0.001)	1.828*** (0.004)	0.793 (0.854)	0.340*** (0.039)	0.161 (0.129)
Saudi income ID_J	1.423*** (0.000)	2.057*** (0.000)	0.792*** (0.000)	0.467*** (0.013)	1.479 (0.479)	2.003*** (0.000)	1.105*** (0.000)	2.550*** (0.000)
Cost of travel CT_{ij}	-0.409*** (0.000)	-0.997*** (0.000)	-1.604*** (0.000)	-0.630*** (0.000)	-0.090 (0.546)	-0.623*** (0.000)	-0.430*** (0.000)	-0.289*** (0.009)
Expatriate workers EXPWOR	2.157*** (0.000)	0.194** (0.088)	1.690*** (0.000)	2.866*** (0.000)	-0.028*** (0.000)	-0.131 (0.261)	1.097*** (0.000)	0.246*** (003)
	Short-run coefficients	-	**Short-run coefficients**	-	**Short-run coefficients**	-	**Short-run coefficients**	-
ECT_{t-1}	-0.601*** (0.000)	-	-0.921*** (0.000)	-	-0.871*** (0.000)	-	-0.675*** (0.000)	-
D(GDP per Capita In Origin Countries)	1.289 (0.605)	-	0.164 (0.667)	-	0.857 (0.875)	-	1.108*** (0.013)	-
D(GDP per Capita In Saudi)	0.875 (0.831)	-	1.901 (0.253)	-	2.841* (0.093)	-	0.247 (0.698)	-
D(Transport Costs)	0.044** (0.044)	-	-1.607 (0.389)	-	0.585** (0.060)	-	0.299*** (0.000)	-
D(Expatriates Workers)	-0.055** (0.058)	-	-2.145*** (0.007)	-	1.203** (0.075)	-	0.008 (0.320)	-
Constant	2.133 (0.127)	-32.427 (0.004)	9.790 0.000	3.590 (0.050)	-1.699 (0.415)	-9.554 (0.064)	-21.767 (0.000)	-41.710 (0.000)
R-squared	-	0.48	-	0.55	-	0.52	-	0.49
Adjusted R-squared	-	0.47	-	0.53	-	0.49	-	0.48
F-statistic Prob(F-statistic)	-	40.246 (0.000)	-	18.093 (0.000)	-	0.081 (0.000)	-	29.059 (0.000)

Chow test	-	18.389 (0.000)	-	13.007 (000)	-	10.657 (0.000)	-	26.452 (0.000)
Lagrange multiplier tests	-	93.711 (0.0000)	-	112.838 (0.000)	-	28.652 (0.002)	-	242.814 (0.000)
Hausman test	-	30.940 (0.000)	-	4.924 (0.002)	-	7.459 (0.003)	-	27.214 (0.025)
Cross-section dependence Breusch-Pagan LM	-	-0.609 (0.542)	-	0.141 (0.887)	-	0.0470 (0.962)	-	4.250 (0.889)
Normal distribution JB probability	-	3.675 (0.159)	-	0.051 (0.974)	-	2.132 (0.344)	-	1.365 (0.505)

Source: Author’s own calculations using EViews. *Note*: *** 1% significant, **5% significant and * 10% significant.

The error correct term ECT_{t-1}values were negative and significant in all four estimators, demonstrating the existence of long-run relationships. The error correction coefficient values (-0.601, -0.921, -0.871, and -0.675) indicate that tourism demand was adjusted for its equilibrium status in every period by -0.60 percent, -0.92 percent, -0.87 percent, and -0.67 percent from the disequilibrium in the t-1 period. This indicates that shocks and deviations from the long-run path were corrected speed towards the equilibrium. Cross-sectional dependence can be tested using the Breusch and Pagan (1980) test under conditions of large T and small N (Pesaran, 2021). Thus, the Breusch and Pagan (1980) test was considered more appropriate for this model. Breusch-Pagan LM tests were conducted under the null hypothesis of cross-sectional independence in the residuals of the regression model. Consequently, the test statistic could not reject the null hypothesis of cross-sectional independence. To choose between POLS, FE and RE models, specification tests were conducted. The Chow test, Lagrange multiplier test, and Hausman test showed that the FE model was the most appropriate to estimate the model.

The income of the destination country was the most influential factor for all international tourism demand in Saudi Arabia. The income of the destination and origin countries positively affected all tourism demand models. In terms of travel costs, it was observed that business tourism demand in this sample was more sensitive to travel costs than other types of tourism demand under investigation. This may be because the countries in the sample are low- and middle-income countries and the cost of travel, especially first or business class, is very important to them. The number of expatriate workers at the destination is one of the most significant tourism demand determinants. This group may have the potential to act as a catalyst for international tourism flows. Expatriate workers had a positive and significant impact on explaining international tourism demand to Saudi Arabia, as expected, in aggregate, business and religious tourism. The results suggest that an increase in the number of expatriate workers in Saudi Arabia would lead to an increase inbound travel demand. As the number of expatriate workers to the destination country increased by 1 percent, the aggregate, business, and religious tourist flow from the origin country increased by 1.097 percent, 1.69 percent, and 1.42 percent respectively. This aligns with the empirical findings of previous research that measured the impact of immigrants on tourism demand. For example, Paniagua and Santana-Gallego (2020) found a positive and robust effect of migration on inbound tourism in the long term. Expatriate workers have a strong connection to the trade theory arguments presented earlier. They play a vital role in reducing trade barriers. By allowing individuals from different countries to settle and work in new environments, it facilitates the exchange of goods, services, and knowledge between nations. Immigrants often bring unique skills, perspectives, and entrepreneurial spirit, leading to increased economic activity and international trade partnerships. However, expatriate workers had a negative and significant impact on VFR tourism demand to Saudi Arabia. This may be due to restrictions on visitor visas. It could also be a result of the low pay and poor working conditions of some expatriate workers, making it difficult for them to bring their family or friends to Saudi Arabia for a visit. In turn, this might impact the image of

Saudi Arabia in expatriate home countries (Al-Emad & Rahman, 2017; Vlieger, 2012). In contrast, Massidda et al. (2015) found that emigrants in Italy had a positive impact on inbound tourism flows for VFR and non-VFR (holiday and business) visitors.

5.8. Summary and conclusion

The main aim of this chapter was to present the investigation into the impact of economic and non-economic factors on aggregate and disaggregate (religious, VFR, and business) tourism demand from 2000 to 2019. Only a limited number of studies on tourism demand have focused on a disaggregate approach by purpose of visit, as compared to an aggregate approach. Therefore, this study provides a significant contribution to the literature on tourism demand by establishing the nature of the impact the variables have on religious, VFR, and business tourism demand.

This study used the GMM estimator for estimating religious tourism demand because the time series (T) was smaller than the cross-section (N). However, the ARDL estimator was used to estimate business, VFR, the aggregated number of tourists, and expatriate workers because T was larger than N. In additional to this, panel regression was used to address any doubts about the validity of unit root tests in small panel data.

This study found that the estimated coefficients were plausible in terms of their expected signs, statistical significance based on economic theory, and the magnitude of the coefficients. The word-of-mouth effect and repeat visits were significant in religious tourism demand. This finding implies that religious tourists who had previously visited Saudi Arabia talked positively of their experience on returning to their home countries, and their experiences tended to stimulate international religious tourism in Saudi Arabia.

Although religious travel was considered primarily a spiritual phenomenon, the income of the origin countries played a critical role in the decision to participate in religious tourism. Overall, the results obtained show the origin country income was a positive and significant variable in all types of tourism demand models. However, when comparing aggregate and disaggregate models, VFR tourism demand showed the highest sensitivity to the income of the origin country, whilst religious tourism was less sensitive to this variable. The cost of living at the destination is an essential factor for explaining all kinds of tourism demand in Saudi Arabia. Religious tourism demand was more sensitive to the cost of living at the destination, whilst business tourism demand was less susceptible to price. While travel cost had an impact on all tourism demand models, the travel cost negatively impacted business tourism demand the most. This study's results confirm that trade between the origin and destination countries is positively related to total and business tourism demand.

Capital investment in the tourism sector positively impacted all tourism demand models. It was a particularly crucial factor for explaining VFR tourism demand. High levels of human rights respect and prosperity in the destination country were significant factors for explaining inbound tourism demand to Saudi Arabia. Specifically, the human rights factor was essential to business tourism demand. Prosperity was more critical to VFR tourism demand. Political risks and relative temperature were significant factors in religious tourism, whilst global health risks had more impact on business tourism. Saudi students studying overseas, and visa restrictions had a more substantial effect on VFR tourism demand. Shared language and religion between the origin country and destination only impacted religious tourism demand. Finally, these findings show that expatriate workers and international students variables significantly impact tourism flows in the Saudi Arabia context, which provides evidence supporting the arguments of trade theory.

CHAPTER 6: FORECASTING ANNUAL TOURISM DEMAND GROWTH RATES IN SAUDI ARABIA

6.1. Introduction

This chapter addresses objective three, as presented in Chapter one of this study. Having estimated the econometric models, this chapter focuses on how these models provide better forecasts than time series models, making comparisons to determine model accuracy. It adds to the knowledge through forecasting tourism demand in the Saudi Arabian context and uses new independent variables. An accurate forecast of international tourist arrivals is crucial for tourism planning and policymaking, and an imperative for destination management (Y.-Y. Liu et al., 2018; Yang & Zhang, 2019), infrastructure development, and tourism investments (Jenkins, 2015). It is also essential to develop policies and plans to manage the resources available to support development initiatives and to allocate limited resources efficiently (Jenkins, 2015). As stated by Song et al. (2019), Uysal and Crompton (1985), and Wandner and Van Erden (1980), the availability of accurate forecasts of international tourism demand is important because of the perishable nature of tourism-related products. This is important when developing countries utilise tourism-led development strategies to promote inclusive economic growth. Several countries, particularly developing countries like Saudi Arabia, set ambitious targets for tourism demand that need accurate forecasting to manage risk and for planning purposes.

This chapter discusses the reasons for forecasting the growth rate of tourism demand and its market share, particularly in the context of periods of expansion and recession. High growth leads to increased demand for resources, whereas low growth leads to low demand for resources. Such a shift in resource demand requires the development of appropriate strategies for risk management in tourism destinations (Kulendran & Wong, 2009). In other words, to effectively manage tourism growth and volatility, it is essential to adequately forecast international visitor arrivals.

Forecasting tourism demand can be categorised into two approaches: time series models and econometric models. Time series models give an easy and relatively accurate forecast of the dependent variable based on its historical values. Econometric models have empirical significance in interpreting changes in tourism demand and exploring the consequences of alternative future policies. However, Song and Li (2008) stated that no one forecasting method had outperformed all other methods in all situations. The inconsistency of performance in time series and econometric models has increased the trend of using combination models for tourism demand forecasting. A combination of various forecasts often exceeds any individual forecasts. Song et al. (2019) found that combining forecasting models leads to increased forecast accuracy. Thus, combined forecasts were used in this study as well as the single forecast methods (time series and econometric models) and provides empirical evidence for comparing the accuracy of combined forecasts versus single forecasts.

This study aimed to develop forecasting models of international tourism demand growth rate for three visiting purposes: religious, business and VFR. The first section of this chapter determines whether the econometric models provided more accurate forecasting than the time series models. The second section determines whether the combined forecast method provides more accurate forecasting than both econometric and time series models. For forecasting purposes, this study considered the following time series models: ARIMA, naive or no change, and exponential smoothing. The econometric forecasting models used were: ARDL, ECM and VAR. The combined forecast models used were SA and VACO combinations. These were applied to combine time series and econometric forecasting models in order to explore the relative efficiency of combining forecasts in the context of tourism demand growth rates. Two forecasting error measures, RMSE and MAPE, were used to compare the forecasting accuracy. Model comparisons were conducted for each purpose of visit separately.

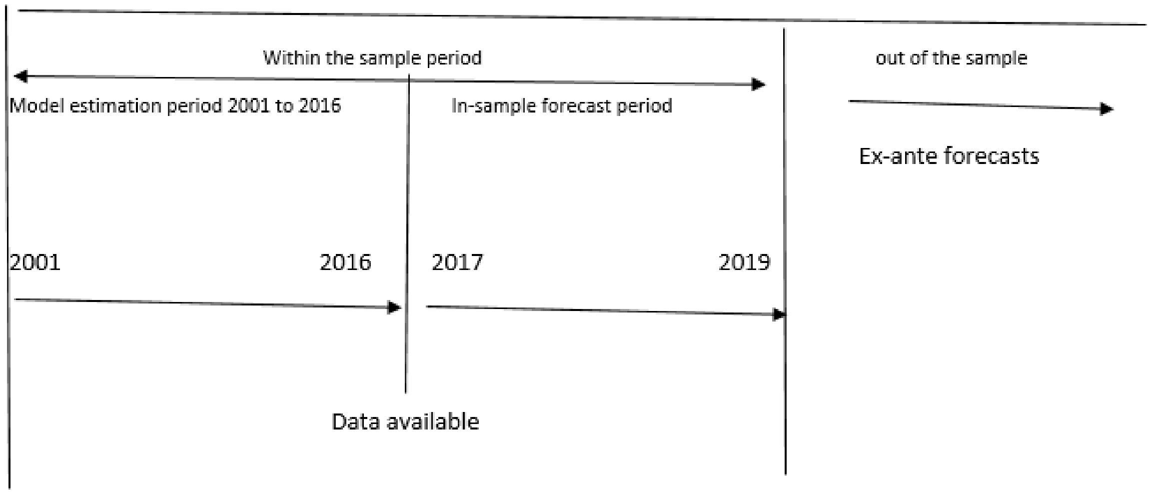
This chapter is structured as follows. Section 6.2 presents a discussion on measuring forecasting accuracy and Section 6.3 outlines the availability of data. Section 6.4 and Section 6.5 discuss the forecasting accuracy of time series models and econometric models, respectively, while Section 6.6 examines the forecasting accuracy of combined models. Section 6.7 concludes the chapter.

6.2. Measuring forecasting accuracy

Before explaining the various measures of forecasting accuracy, it is necessary to clarify two related forecasting concepts: within-sample period forecasting and out-of-sample forecasting. The distinction between these two concepts is associated with the different predicting reference points. According to Frechtling (2001), the total sample period can be divided into model estimating periods and within the sample forecasting periods.

In this study, the model was estimated using available data from 2001 to 2016. Within the sample forecasting period, the model forecast was generated from 2017 to 2019 and compared with the actual value. In this case, the actual values of the explanatory and dependent variables during the forecasting period were already known. On the other hand, out of the sample period where the forecast was generated for variables that had unknown values (before the event occur) . As the aim of this study was to assess the accuracy of the model forecasts, the focus was on a within-sample period forecast. Comparing forecasting accuracy generated from within-sample period forecasts can assist researchers in assessing which approach produces the best forecasts (Peng et al., 2014; Song & Witt, 2000).

Figure 6.1. Estimation period within the sample forecast period



6.2.2. The forecasting errors.

The accuracy of forecasting models is based on how close forecast values are to the actual value. A forecasting error is the difference between the actual and forecast values over the forecasting horizon. It can be used to assess the accuracy of forecasting models and is defined as:

$$e_t = Y_t - F_t \qquad (6.1)$$

Where, e_t is the forecasting errors in time t.Y_t the actual value of tourist arrivals growth rate in time t is F_t is the forecast value of tourist arrivals in time t

Theoretically, with a well-defined model, forecasting errors are expected to have a mean of zero over a given forecast horizon. However, very small forecasting errors can be obtained, even for not well specified models, due to the existence of positive and negative forecasting error values that cancel each other out. To address this problem, the accuracy of the forecasting error measurements was improved, and the equation error (6.1) was modified to squared values (e_t^2), as in this RMSE equation:

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(Y_t - F_t)^2}{n}} \qquad (6.2)$$

Where Y_t is the actual values, F_t is forecast values and n denotes the number of forecasts for evaluation. Thus, RMSE is more sensitive to one particularly bad forecast (Li et al., 2005).

MAPE is another error forecast measure in which the forecast errors are divided by the real values of the demand for tourism in order to generate unit independent measures (percentage errors). The researcher can then compare the errors of the fitted models that vary on the level. This is shown in the following equation:

MAPE=$\frac{1}{N}\sum_{t=1}^{N}\left|\frac{Y_t - F_t}{Y_t}\right| \times 100$ (6.3)

MAPE and RMSE have been commonly applied in the forecasting literature. For example, Jiao et al. (2021), Volchek et al. (2019), and Wen et al. (2020) have explained why MAPE and RMSE are appropriate measures for assessing the predictive accuracy of tourism demand models. One advantage is that they do not depend on the magnitude of the demand variables that are being predicted. In practice, researchers are usually interested in forecasting tourism in one of two directions: either outbound travel demand from a particular origin to a number of destinations, or inbound tourism demand to a specific destination from numerous tourist-generating countries (unit to unit). The demand variables magnitude is likely to vary from country to country (unit to unit). Using unit-independent measures allows us to compare the accuracy of forecasts not only between models but also between countries (units). The current study employed MAPE and RMSE to examine forecast performance across different approaches.

6.3. Data

This study considered the annual tourism demand growth rate of dependent and independent variables. In econometrics models, both economic and non-economic variables were included as tourism demand determinants. The tourism demand growth rate was estimated from 2001 to 2016. The re-estimation approaches were considered to generate a one year a head forecast from 2017 to 2019.

The growth rate data was obtained by following these steps:

Step 1: The growth rate of each country was derived from = lny_t-lny_{t-1}. (6.4)

Where = lny_t is the current period and lny_{t-1} is the previous period.

Step 2: The market share of each country (m_i) was calculated by dividing the number of tourists from an origin country by the total number of tourist arrivals to Saudi Arabia for each purpose of visit separately over the same period.

Step 3: The total market share growth rate of tourism demand was obtained by using this formula:

$$\sum_{i=1}^{n} m_i \; growth\; rate_i \qquad (6.5)$$

Where $m_i =$ market share growth rate of tourism demand.

The same steps were applied to obtain other variables' market share growth rates and each purpose of visit separately.

6.4. Forecasting tourism demand growth rates with time series models

Three time series models were employed in this study to forecast the growth rate of international tourist arrivals from major source markets to Saudi Arabia: ARIMA, naive or no change, and exponential smoothing. These models were chosen for this research because they have been widely utilised to forecast tourism demand (Li et al., 2005).

6.4.1. Autoregressive integrated moving average (ARIMA) models to forecast tourism demand growth rates.

ARIMA models combine three types of processes: the autoregressive (AR) model; differencing to achieve the stationarity of the time series model; and the moving average (MA) model. This ARIMA model was developed by George Box and Gwilym Jenkins in 1970 (Box et al., 2015). It has been widely utilised in forecasting. ARIMA can generate accurate short-term forecasts (Baldigara & Mamula, 2015; Fattah et al., 2018). Additionally, it can assist users in understanding the characteristics and dynamic behaviour of time series (Yang & Zhang, 2019). In the ARIMA model, the current value of the series is linearly dependent on its own previous values as well as a combination of the current and previous values of a white noise error term. It is represented by the formula ARIMA model (p, d, q), where p is the number of autoregressive terms, d is the number of differences, and q is the number of moving averages. ARIMA becomes an ARMA (p, q) model if the time series data is stationary at level (Gujarati & Porter, 2009). Given a stationary time series Y_t, the ARMA (p, q) model combines the above AR (p) and MA (q) processes, and is written as follows:

$$Y_t = \alpha_0 + \theta_1 Y_{t-1} + \theta_2 Y_{t-2} + \ldots + \theta_p Y_{t-p} + \gamma_1 u_{t-1} + \gamma_2 u_{t-2} + \ldots + \gamma_q u_{t-q} + u_t \quad (6.6)$$

Where θ *and* γ are the coefficients of the autoregressive operator (p) and moving average operator (q) respectively. P is the order of autoregressive process and q the order of moving averages.

The ARMA models were applied for all three visiting purposes (religious, business, and VFR).

6.4.1.1. ARMA model estimation growth rates of religious, business and VFR tourist arrivals

This section is divided into three sub-sections based on the Box–Jenkins procedure: check the stationarity, Identify the model and estimation, and then Forecasts.

Stationarity

The ARMA model was applied to the growth rate of religious, business, and VFR tourists arriving in Saudi Arabia from 2001 to 2016, to generate forecasting for 2017 to 2019. First, to assess whether or not the data satisfied a stationary process, the ADF test for stationarity, also known as the unit root test, was conducted. The ARMA model is only appropriate when the series is stationary. Therefore, it was necessary to check stationarity.

Table 6.1. ADF test to examine the null hypothesis that the growth rate of religious, business, and VFR tourist arrivals to Saudi Arabia had a unit root, 2001 to 2016

Type of tourism	ADF test statistic		Decision
Religious	**T-Statistics**	**-4.289*** Prob=0.009**	The null hypothesis was rejected at the 5 percent level - religious tourist arrival time series data is stationary at the level.
	1% level	-4.167	
	5% level	-3.733	
	10% level	-3.310	
Business	**T-Statistics**	**-4.669*** Prob=0.001**	The null hypothesis was rejected at the 5 percent level – business tourist arrival time series data is stationary at the level.
	1% level	-4.616	
	5% level	-3.710	
	10% level	-3.297	
VFR	**T-Statistics**	**-4.936*** Prob=0.006**	The null hypothesis was rejected at the 5 percent level – VFR tourist arrival time series data is stationary at the level.
	1% level	-4.667	
	5% level	-3.733	
	10% level	-3.310	

Note: *** 1% significant, **5% significant and * 10% significant.

Table 6.1 shows the outcomes of the ADF test on religious, business, and VFR growth rates for tourist arrivals to Saudi Arabia. The null hypothesis was that the series under examination had a unit root. It can be seen that the ADF p-value was significant. Therefore, the null hypothesis was rejected, and the series had a stationarity at level. Consequently, the ARIMA model became an ARMA model in this study.

Identify the model and estimation.

After verification of the stationarity of the series, the value of the parameters p and q of the ARMA model needed to be identified. This could be determined using the autocorrelation coefficient function plot (ACF) and partial autocorrelation coefficient function plot (PACF). Several models needed to be tested to identify the most appropriate model. The ACF and PACF results for the religious, business, and VFR inbound tourist arrival series are shown in Figure 6.2. Most of the values of the ACF and PACF were within the 5 percent critical boundary and the correlogram analysis shows that there is no probability of a stationarity problem. Since the time series was stationary, the ARMA model could apply, and the parameter values were estimated. The ACF and PACF graphs were used to determine the number of autocorrelation and partial autocorrelation coefficients with a level of significance. The basic model of the series could be selected in this step. The order of MA (q) was selected using the ACF function, and the order of AR (p) was selected using the PACF function (Fattah et al., 2018).

Figure 6.2. Autocorrelation and partial autocorrelation functions for Religious, Business and VFR tourist arrival growth rates from 2001 to 2019

Religious

	AC	PAC	Q-Stat	Prob
1	-0.191	-0.191	0.8112	0.368
2	-0.375	-0.427	4.1124	0.128
3	-0.160	-0.438	4.7546	0.191
4	0.333	-0.046	7.7077	0.103
5	-0.016	-0.203	7.7152	0.173
6	-0.086	-0.093	7.9405	0.242
7	-0.005	0.009	7.9414	0.338
8	-0.085	-0.264	8.2018	0.414
9	0.199	0.151	9.7761	0.369
10	-0.109	-0.164	10.300	0.415
11	0.019	0.013	10.319	0.502
12	-0.092	-0.032	10.800	0.546

Business

	AC	PAC	Q-Stat	Prob
1	-0.206	-0.206	0.9387	0.333
2	-0.396	-0.458	4.6157	0.099
3	0.023	-0.251	4.6288	0.201
4	0.174	-0.112	5.4323	0.246
5	-0.034	-0.120	5.4657	0.362
6	-0.119	-0.155	5.8984	0.435
7	-0.083	-0.281	6.1267	0.525
8	0.218	-0.037	7.8487	0.448
9	0.113	0.069	8.3538	0.499
10	-0.171	0.019	9.6486	0.472
11	-0.064	0.040	9.8544	0.544
12	-0.034	-0.174	9.9204	0.623

VFR

	AC	PAC	Q-Stat	Prob
1	-0.480	-0.480	5.1152	0.024
2	-0.030	-0.339	5.1359	0.077
3	0.352	0.250	8.2230	0.042
4	-0.174	0.215	9.0244	0.060
5	0.048	0.173	9.0896	0.106
6	-0.025	-0.128	9.1091	0.168
7	0.009	-0.145	9.1120	0.245
8	-0.020	-0.138	9.1272	0.332
9	0.001	0.028	9.1272	0.426
10	-0.105	-0.112	9.6206	0.474
11	0.034	-0.095	9.6779	0.560
12	-0.050	-0.154	9.8180	0.632

Several models were tested to identify the most appropriate models of ARMA (p, q). The order of the AR and MA functions was determined using the results shown in Figure 6.2.

The possible group of ARMA (p, q) models for tourism demand growth rate were determined to be:

- **Religious:** ARMA (2, 2), ARMA (2, 4), ARMA (3, 2), ARMA (3, 4).
- **Business**: ARMA (1, 1), ARMA (2, 1), ARMA (1, 2) and ARMA (2, 2), ARMA (3, 1), ARMA (3, 2) and ARMA (7, 2).

- **VFR**: ARMA (1, 1), ARMA (1, 3), ARMA (2, 3) and ARMA (2, 1).

Some statistical measures were used to assist in selecting the most appropriate ARMA model for the forecast. Selection was based on a large number of significant coefficients, the lowest value of the AIC and Schwarz information criterion (SIC), and the highest Adj R^2 value.

Table 6.2. Evaluation of various models for religious, business and VFR tourists arrival growth rates from 2001 to 2016

	Religious				Business				VFR			
Name of model	$\boldsymbol{ARMA^{1}}$ **(3, 2)**	$ARMA^{2}$ (2,2)	$ARMA^{3}$ (2,4)	$ARMA^{4}$ (3,4)	$\boldsymbol{ARMA^{1}}$ **(2,2)**	$ARMA^{4}$ (1,1)	$ARMA^{2}$ (3,1)	$ARMA^{3}$ (1,2)	$ARMA^{3}$ (1,1)	$\boldsymbol{ARMA^{1}}$ **(1,3)**	$ARMA^{4}$ (2,3)	$ARMA^{2}$ (2,1)
AIC	**-0.33**	-0.283	-0.27	-0.183	**- 1.662**	-1.431	-1.581	-1.597	-0.17	**-0.261**	-0.099	-0.204
SIC	**-0.137**	-0.09	-0.077	-0.009	**-1.389**	-1.351	-1.388	-1.354	-0.371	**-0.406**	-0.093	-0.397
Adjusted R-square	**0.245**	0.206	0.182	0.108	**0.529**	0.357	0.507	0.345	0.31	**0.618**	0.4211	0.374
Standard error of the regression	**0.155**	0.188	0.181	0.179	**0.047**	0.074	0.082	0.089	0.101	**0.132**	0.113	0.099
Significant coefficient	**3**	2	0	2	**3**	1	3	2	1	**2**	1	1

Note: The table does not include the less appropriate models in business tourism demand. These models were ranked based on the order of best models.

Table 6.2 shows that the ARMA (3, 2), ARMA (2,2), and ARMA (1,3) for the growth rates of religious, business, and VFR tourism demand models successfully passed the selection criteria discussed above. Thus, these models were considered the most efficient to forecast the growth rate of tourism demand in Saudi Arabia. A residual randomness test was performed on the estimation result. If it passed the test, the models could be chosen as the optimal models. However, if the estimation result did not pass the test, the second-smallest AIC value and SIC value were selected, and the applicable statistical test was performed until the most appropriate model was found.

The selected forecasting models ARMA (3, 2) ARMA (2, 2), and ARMA (1,3) for religious, business, and VFR growth rate, respectively, are shown in Table 6.3. Goodness-of-fit tests were carried out to validate that the models were appropriately calibrated.

Table 6.3. Forecasting ARMA models for religious, business and VFR tourist arrival growth rates from 2001 to 2016

Variable	Religious	Business	VFR
Model identified	**ARMA (3,2)**	**ARMA (2,2)**	**ARMA (1,3)**
C	0.055*** (0.000)	0.095*** (0.018)	0.085*** (0.004)
AR	0.433*** (0.006)	-0.999*** (0.000)	-0.734*** (0.019)
MA	0.261*** (0.004)	0.529*** (0.000)	0.963 (0.999)
Model estimate	$y_{t=}$0.055 +0.433y_{t-3}-- 0.261ε_{t-2}	$y_{t=}$0.095-0.999y_{t-2}+ 0.5291ε_{t-2}	$y_{t=}$0.085 -0.734y_{t-1}+ 0.963 ε_{t-3}
Adjusted R-square	0.245	0.529	0.618
F statistic: Prob (F-statistic)	5.412 (0.021)	10.677 (0.001)	8.908 (0.002)
JB	1.187 (0.552)	1.072 (0.505)	2.858 (0.239)

. *Note*: *** 1% significant, **5% significant and * 10% significant.

As evident in Table 6.3, the AR and MA coefficients were significant, and the probabilities were less than 0.05. The non-significance of the JB statistic implies that the residuals were normally distributed. To further validate the model's suitability, Figure 6.3 illustrates the correlogram (autocorrelations and partial autocorrelations) of the standardised residuals and the squared standardised residuals, confirming that the residual was white noise. The null hypothesis was that residuals are white noise and the probability is more than 5 percent. This means that the null hypothesis could not be rejected. The model was used to generate forecasting values from 2017 to 2019.

Figure 6.3. Autocorrelation and partial autocorrelation function graphs of the residual series - Residual Q statistic probabilities of ARMA models for the growth rate of religious, business and VFR tourism demand

Religious

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.249	-0.249	1.1934	
		2	-0.188	-0.267	1.9240	
		3	-0.162	-0.331	2.5085	0.113
		4	0.091	-0.165	2.7065	0.258
		5	0.003	-0.188	2.7067	0.439
		6	0.004	0.166	2.7071	0.608
		7	0.098	0.008	3.0125	0.698
		8	-0.156	-0.202	3.8840	0.692
		9	0.158	0.086	4.9082	0.671
		10	-0.142	-0.131	5.8770	0.661
		11	0.095	0.019	6.3979	0.700
		12	-0.102	-0.093	7.1405	0.712

Business
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.032	-0.032	0.0202	
		2	-0.204	-0.205	0.8735	
		3	-0.152	-0.175	1.3886	0.239
		4	0.139	0.085	1.8547	0.396
		5	-0.035	-0.095	1.8866	0.596
		6	-0.096	-0.092	2.1503	0.708
		7	-0.048	-0.052	2.2248	0.817
		8	0.173	0.109	3.3063	0.770
		9	0.190	0.191	4.7979	0.685
		10	-0.275	-0.231	8.4297	0.393
		11	-0.161	-0.090	9.9226	0.357
		12	-0.053	-0.154	10.127	0.429

VFR

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.197	-0.197	0.7441	
		2	-0.254	-0.304	2.0685	
		3	0.153	0.031	2.5839	0.108
		4	0.088	0.065	2.7703	0.250
		5	-0.008	0.093	2.7720	0.428
		6	-0.022	0.035	2.7859	0.594
		7	-0.054	-0.059	2.8806	0.718
		8	-0.145	-0.226	3.6368	0.726
		9	0.123	-0.006	4.2593	0.749
		10	-0.086	-0.148	4.6150	0.798
		11	-0.063	-0.023	4.8410	0.848
		12	-0.087	-0.164	5.3859	0.864

Forecasting

Forecasts from the identified models shown in Tables 6.3 were compared using RMSE and MAPE. The results are presented in Table 6.4.

Table 6.4. Forecasting of ARMA models for all visitor purposes from 2017 to 2019

Purpose of visit	ARMA model	RMSE	MAPE
Religious	ARMA (3, 2)	0.0341(1)	18.661(1)
Business	ARMA (2, 2)	0.1162(3)	38.971(2)
VFR	ARMA (1,3)	0.0853(2)	39.801(3)

As evident in Table 6.4, based on RMSE and MAPE, ARMA gives the best forecast of growth rates for religious tourism demand, followed by business, and then VFR tourism demand.

6.4.2. Single exponential smoothing (SES) model to forecast tourism demand growth rates.

The exponential smoothing forecasting techniques was developed by Brown (1957) and Holt (1957). One of the basic concepts of smoothing models is to generate forecasts of future values as weighted averages of previous observations, with more recent observations holding a greater weight in determining projections. By constructing forecasts using weighted averages, this study employed this smoothing technique.

The single exponential smoothing (SES) approach is used when there is no trend and no seasonality in the time series. In this study, growth rate data did not extend to trend and seasonality. The specific formula for SES is:

$$\mathrm{F}_{t=}\alpha y_t + (1-\alpha)F_{t-1} \qquad (6.7)$$

Where y_t is the actual value for time period t, F_t is the forecast value of the variable y for time period t. α is the smoothing constant (0< α<1). The forecast f_t is based on weighting the most recent forecast F_t $with\ a\ weight\ of\ (1-\alpha)$ (Hedi & Merawati, 2020; Yonar et al., 2020).

Table 6.5. RMSE values of the SES model with different values of α, 2001 to 2016

Forecast method	Religious RMSE	Business RMSE	VFR RMSE
∝=0.2	0.189(1)	0.484(1)	0.286(1)
∝=0.3	0.198(2)	0.499(2)	0.299(2)
∝=0.4	0.207(3)	0.522(3)	0.315(3)
∝=0.5	0.216(4)	0.546(4)	0.332(4)
∝=0.6	0.220(5)	0.569(5)	0.352(5)
∝=0.7	0.239(7)	0.594(6)	0.373(6)
∝=0.8	0.234(6)	0.618(7)	0.396(7)

The choice of an error measure has a significant impact on the conclusions about which of a set of forecasting methods is the most accurate. The speed at which the older responses are dampened (smoothed) depends on the value of α. When the smoothing constant is close to 1, dampening seems to be quick, and when it is close to 0, dampening seems to be slow. Typically, the RMSE can be used as a criterion for selecting an appropriate smoothing constant (Newaz, 2008). For example, by assigning values ranging from 0.1 to 0.99, we can choose the value that produces the smallest RMSE.

SES models were tested for different α values. Table 6.6 provides a summary of SES outputs. SES of α = 0.2 has the smallest RMSE for the three types of tourism. Thus, the best model among other single exponential model with the smallest RMSE = 0.189, 0.484 and 0.286 with a weight of α = 0.2.

Table 6.6. Forecasting accuracy of the exponential smoothing models from 2017 to 2019

Religious		Business		VFR	
RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
0.028(1)	16.818(1)	0.161(3)	44.179(3)	0.073(2)	34.273(2)

In this study, the forecasting performance for each purpose of visiting was compared separately. Table 6.7 provides a summary of the results of the exponential smoothing approach. Since the rule of thumb is that smaller MAPE and RMSE results are better, the best forecasting was for religious tourism demand, in terms of both RMSE and MAPE, followed by VFR, and then business tourism demand. The rankings for religious, business, and VFR tourism demand were the same across MAPE and RMSE.

6.4.3. Naive-1 or no change model to forecast tourism demand growth rates.

The naive-1 or no change forecasting model suggests that the forecast value for a period (F_t) is equal to the observed value for the previous period (Y_{t-1}). The specific formula for this method is:

$F_{t=}Y_{t-1}$ (6.8)

$F_{t=}current\ forecast\ value$, Y_{t-1} $is\ previous\ period$

The naive-1 model was used as a benchmark to compare with the other models with the same features, such as the smoothing exponential and ARMA.

The forecasting accuracy of the naive-1 approach can be seen in Table 6.8. MAPE and RMSE resulted in the same ranking for VFR tourism. The MAPE and RMSE associated with naive-1 or the no change model indicates that this is the best model for forecasting VFR tourism demand.

Table 6.7. Forecasting accuracy of naive-1 models from 2017 to 2019

	Religious		Business		VFR	
Naive approach	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
	0.065(2)	49.953(3)	0.228(3)	40.966(2)	0.062(1)	26.652(1)

As shown in Table 6.8, the SES model was the best for forecasting the growth rate of religious demand, based on the outcomes of RMSE and MAPE. Naive-1 was the best model for forecasting the growth rate of VFR tourism demand. For the growth rate of business tourism demand, however, MAPE and

RMSE resulted in different rankings for best-performing models. Based on the MAPE, the ARMA was the best model, but based on the RMSE, the exponential smoothing model was the best.

Table 6.8. Forecasting of the time series models, exponential smoothing models, ARMA and no change models, 2017 to 2019

Forecast models	Religious		Business		VFR	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Exponential smoothing models	0.028(1)	16.818(1)	0.161(1)	44.179(3)	0.073(2)	34.273(2)
ARMA	0.0341(2)	18.661(2)	0.1162(2)	38.971(1)	0.0853(3)	39.801(3)
Naive-1	0.065(3)	49.953(3)	0.228(3)	40.966(2)	0.062(1)	26.652(1)

6.5. Forecasting tourism demand growth rates with econometric forecasting models

Econometric forecasting models have contributed to the investigation of causal links between determinants of international tourist arrivals and tourism demand in a variety of empirical situations. The emphasis of econometric models is on demonstrating the structure of causality and measuring the impact of various explanatory variables on future demand. Modelling begins by specifying potential causality (as suggested by demand theory). To model and then forecast tourism demand from the source markets to Saudi Arabia, this study employed three econometric models: ECM, VAR and ARDL.

6.5.1. The error correction model (ECM)

Engle and Granger (1987) were the first to develop the ECM. In this study, this model was employed to explore the long-run relationship between tourism demand and its impacting factors, as well as the short-run error correction mechanism in determining tourism demand. Kulendran and Witt (2001), and Lim and McAleer (2001) provided in-depth reviews of this method and its uses in the tourism sector. The ECM can be applied for policy analysis and forecasting. Diagnostic tests for normality, serial correlation, heteroscedasticity, functional form, and structural stability are used to assist in choosing the best model. First, an ADF unit root test was implemented to determine the order of integration in the variables. The results showed that some of the variables were stationary at a level while others were on the first difference I(1). Second, the Johansen test determined the cointegrated vectors in the system. The relationship was shown to be cointegrated, and the long-run elasticities were estimated. Since the cointegrating relationship among the variables was identified, the next step was to construct an ECM to identify the short-run relationships among the variables.

6.5.2. The vector autoregressive (VAR) model

The VAR approach is a system estimation technique and was first proposed by Sims (1980). The majority of traditional tourism demand models consider explanatory variables to be exogenous in a regression model, whereas the VAR model is a system of equations in which all variables are considered endogenous. VAR is employed when there is uncertainty about a distinction between endogenous and exogenous variables, or when forecasters or practitioners are concerned about the effect of policy 'shocks' on forecasting (Shen et al., 2008; Song & Witt, 2000).

VAR models have the ability to make accurate predictions (Song & Witt, 2006) and are preferable to the single equation for the following reasons (Wong et al., 2006). To begin with, VAR models do not necessitate an inherent theoretical basis for their development and estimation. Second, they do not require projections of the explanatory variables to be produced initially to generate the projections of the dependent variable. Nevertheless, although the VAR model has been extensively and successfully employed in macroeconomics, very few studies have applied VAR models to tourism forecasting. Song and Witt (2006), and Veloce (2004) are among the few that did use this model to forecast tourist demand.

All explanatory variables except the constant, time trend and dummies were considered endogenous in this study.

6.5.3. The autoregressive distributed lag (ARDL) model

Since the sample size in this study was small, the ARDL was chosen, as discussed in Chapters four and five. Moreover, ARDL can estimate long-run and short-run tourism demand relationships. It is also able to distinguish between dependent and independent variables and allow for tests of the existence of relationships between variables at different levels, regardless of whether the underlying regressors are purely I(0), I(1), or mutually cointegrated.

6.5.4. Estimation of econometric models for forecasting

This section provides the estimation of the three econometric models (ECM, ARDL and VAR). First, the models were estimated from 2001 to 2016 and insignificant variables were excluded one by one from the equation. Typically, the least significant variable with the lowest t statistic is removed from the model during the procedure, and the reduced model is re-estimated. This procedure is repeated until all remaining coefficients of the variables are correct. The results of this procedure, as conducted in this study, are presented in Table 6.9.

Typically, when making a selection, the final model should be satisfied, with no autocorrelation, no heteroscedasticity, and non-normality, and the function form should be specified correctly. The following diagnostic tests were used in this study: the Lagrange multiplier test for serial correlation (Breusch, 1978; Godfrey, 1978); the JB test for non-normality (Jarque & Bera, 1980); the RESET test for misspecification (Ramsey, 1969); and the White test for heteroscedasticity (White, 1980). Several criteria were used to decide on the optimal lag length for the VAR model, including the likelihood ratio (LR), the adjusted LR, the AIC, and the SBC. Selecting the appropriate lag structure for the model was crucial because having too many lags would result in the loss of degrees of freedom, while too few lags would not accurately represent the data-generating process (Song & Witt, 2000). The VAR model's maximum lag length was set to two in order that the identifying the appropriate lag models. The results suggest the lag length of VAR models is one.

As shown in Table 6.9, the coefficients of the of origin countries income variable had the expected positive signs and significance at 1 percent, 5 percent and 10 percent in all models. This implies that the income of the origin countries is one of the most important factors to impact the growth rate of tourism demands to Saudi Arabia, for all visiting purposes. As expected, the cost of living at the destination and travel costs significantly and negatively impacted the growth rate of inbound tourism demand. The estimated coefficients of political risks had a significant impact and were negative. Human rights coefficients were significant, with positive signs in all the models. In terms of global health risks in the ARDL estimated, it had a significant negative impact only on the business and religious growth rate of tourism demand in ECM estimate, global health risks had a significant negative impact on VFR, in VAR estimated it had a significant negative impact religious and VFR tourism demand models.

As can be seen in table 6.9 the VAR model, two diagnostic tests, the Lagrange multiplier test and the RESET test, were not available in the EViews software. Diagnostic test results show that all models passed all diagnostic tests. The Durbin-Watson stat was in the range of acceptance of 1.5 to 2.5. The adjusted R-squared range was between 70 and 93, which is relatively high. This study used diagnostic checking due to its importance in econometric modelling.

The estimation results of VAR, ECM and ARDL were satisfactory and were used to generate forecasts.

Table 6.9. Estimates of ARDL, ECM, and VAR econometric models of religious, business and VFR tourism demand growth rates, 2001 to 2016

Variable	ARDL			ECM			VAR		
	Religious	**Business**	**VFR**	**Religious**	**Business**	**VFR**	**Religious**	**Business**	**VFR**
Origin income	0.641*** (0.002)	0.517* (0.086)	1.080** (0.011)	0.322** (0.002)	0.671* (0.301)	2.687* (0.091)	1.152*** (0.001)	0.010* (0.089)	0.358*** (0.030)
Cost of living at destination	-1.529** (0.024)	-0.008 (0.881)	-0.621 (0.078)	-0.724* (0.089)	-0.0464 (0.089)	-1.550*** (0.013)	-0.541 (0.340)	-0.0745* (0.084)	-0.588** (0.051)
Cost of travel	-0.038** (0.051)	-0.713** (0.062)	-0.039* (0.085)	-0.836)*** (0.000)	-1.481*** (0.005)	-0.589*** (0.024)	- 0.836* (0.084)	- 0.664 (0.388)	-0.145*** (0.029)
Political risks	-0.057*** (0. 014)	-1.006* (0.082)	-2.106* (0.080)	-0.048 (0.201)	-0.089 (0.645)	-2.047 (0.320)	-0.282** (0.095)	-0.003*** (0.013)	0.137** (0.051)
Human rights index	0.0317** (0.052)	0.094*** (0.036)	0.227 (0.268)	0.516*** (0.023)	1.073*** (0.000)	0.308 (0.398)	0.200*** (0.023)	0.037** (0.061)	0.028** (0.072)
Global health risks	-0.013* (0.085)	-0.099* (0.094)	-0.0001 (0.997)	-0.048 (0.201)	-0.094 (0.212)	-0.128*** (0.022)	-0.060*** (0.012)	-0.788 (0.244)	-1.059** (0.069)
$\overline{R}^2$	0.805	0.929	0.882	0.789	0.703	0.860	0.753	0.858	0.865
NORM	P=(0.666)	P=(0.981)	P=(0.239)	P=(0.898)	P=(0.299)	P=(0.526)	P=(0.431)	P=(0.329)	P=(0.971)
Heteroscedasticity	P=(0.298)	P=(0.984)	P=(0.998)	P=(0.912)	P=(0.658)	P=(0.979)	P=(0.207)	P=(0.946)	P=(0.350)
RESET	P=(0.417)	P=(0.888)	P=(0.973)	P=(0.762)	P=(0.145)	P=(0.086)	not available		
LMSC	P=(0.513)	P=(0.352)	P=(0.035)	P=(0.682)	P=(0.467)	P=(0.148)	not available		

Note: P value are presented in parentheses ***, **, * indicate significance at the 1%, 5% and 10% levels respectively.

6.5.5. Forecasting comparison of ARDL, ECM and VAR models

In this section, the forecasting performance of ARDL, ECM and VAR models are estimated and compared.

Table 6.10: Forecasting comparison of ARDL, ECM and VAR models based on RMSE and MAPE, 2017 to 2019

Models	Religious		Business		VFR	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
ECM	0.035(1)	17.827(1)	0.142(1)	45.036(2)	0.047(1)	15.806(1)
VAR	0.040(2)	22.921(2)	0.399(3)	41.169(1)	0.134(3)	95.897(3)
ARDL	0.066(3)	26.808(3)	0.302(2)	74.073(3)	0.097(2)	57.472(2)

Table 6.10 presents the performance of forecasts for tourism demand growth rates in Saudi Arabia using ARDL, ECM and VAR models. The MAPE and RMSE gave the same ranking for 67 percent (6 of 9) of the cases. The ECM forecasts performed best, with the lowest MAPE and RMSE for all visiting purposes (except MAPE in the business tourism demand growth rate). This result aligns with Kim and Song (1998), and Song et al. (2000), who found that the ECM outperforms other models in terms of forecasting performance. Kulendran and Witt (2001) investigated the performance of ECM in comparison to other time series models, including univariate ARIMA models and BSMs. They also noted that ECM outperforms other models in the majority of cases. Ouerfelli (2008) forecast quarterly European tourism demand using cointegration analysis and ECM and their empirical evidence suggested that ECM provides precise forecasts.

A primary objective of this thesis was to find the best predictive performance model between time series and econometric models. The results of the analysis are summarised in Table 6.11.

Table 6.11. Forecasting of times series models and econometric models using RMSE and MAPE, 2017 to2019

Mo	Forecast model	Religious		Business		VFR	
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Time series model	ARMA	0.034(2)	18.661(3)	0.116(1)	38.971(1)	0.0853(4)	39.805(4)
	Exponential smoothing Model	0.028(1)	16.818(1)	0.161(3)	44.179(4)	0.0731(3)	34.276(3)
	Naive Approach	0.067(6)	49.953(6)	0.229(4)	40.966(2)	0.062(2)	26.652(2)
	Average	**0.043(1)**	**28.478(2)**	**0.168(1)**	**41.372(1)**	**0.0736(1)**	**33.576(1)**
Econometric	An ECM	0.035739(3)	17.827(2)	0.1420(2)	45.036(5)	0.0472(1)	15.806(1)
	Vector autoregression (VAR)	0.0406(4)	22.921(4)	0.399(6)	41.169(3)	0.1345(6)	95.897(6)
	ARDL	0.0668(5)	26.808(5)	0.302(5)	74.073(6)	0.097(5)	57.472(5)
	Average	**0.047(2)**	**22.519(1)**	**0.2814(2)**	**53.426(2)**	**0.092(2)**	**56.391(2)**

In general, the smaller the MAPE and RMSE, the more accurate the model's forecasts. The MAPE and RMSE results for the time series model were less than for other econometric models. On average, the time series models performed better for 83 percent of cases (5 of 6), while the econometric models performed better for 17 percent of cases (1 of 6). This result aligns with the findings of Cranage and Andrew (1992), that the performance of time series models was similar to, or even better than, that of econometric models. However, this current study's results contrast with the work of Nosier (2012), who found that econometric models outperform time series models and produce highly accurate forecasts.

As evident in Table 6.11, econometric forecasting is associated with poorer forecasts than time series forecasting when any causal variables themselves need to be forecasted. Time series models (univariate methods) are more accurate than econometric models since there is less likelihood of forecast error (Oh & Morzuch, 2005). Chan et al. (1999), Du Preez and Witt (2003), and Kulendran and Witt (2001) compared the forecasting capabilities of time series approaches and found that they tend to outperform traditional econometric models.

Comparing the several estimated measures of forecasting errors in time series and econometric models, the RMSE and MAPE gave the same ranking in 11 out of 18 cases, which represents 61 percent of cases. The MAPE and RMSE ranked differently in 7 out of 18 cases, which represents 39 percent of cases. However, on average, the RMSE and MAPE gave the same ranking in four out of six cases, which represents 67 percent of cases, they ranked differently in two out of six cases, which represents 33 percent of cases.

6.6. The combined forecasting method

There are two distinct forecasting methods: the time series and econometric forecasting approach (which generates direct forecasts from a single model from past data); and the econometric and combination forecasting method (which generates composite forecasts by merging individual forecasts). The ambiguity of performance in the previous forecasting of time series and econometric models has encouraged the development of a trend towards a combined method for tourism demand forecasting. In their ground-breaking study of forecast combinations in the tourism industry, Fritz et al. (1984) argued that combining many competing forecasts might decrease errors and enhance overall accuracy. One important step in a combination is identifying the optimal weights assigned to each constituent projection. The main combination methods vary in the way they use historical data to compute the weights. This study used the most common statistical weighting systems, the SA and the VACO methods (Li, 2004), discussed below.

6.6.1. The simple average (SA) combination method

A simple procedure to combine the forecasts is to take an arithmetic average of the forecasts. This procedure can be used as a useful reference point (benchmark) and it has been shown to perform better than some other complicated methods (Makridakis & Winkler, 1983). The SA method does not consider the historical performance of the individual forecasts when calculating the composite forecasts, since the combined weight is spread fairly among all the individual forecasts. The SA method can be written as:

$$f_{ct} = \sum_{i=1}^{n} \frac{f_{it}}{n}, \qquad (6.9)$$

Where, f_{ct} denotes the combined forecast , f_{it} is the individual forecast in time period t, f_{ct} is the combined forecast generated by the n individual forecasts f_i, and n is the number of forecasts to be combined. The SA method, known also as the "folk theorem" in the literature on forecast combinations, assigns equal weight to each individual forecast rather than utilising the optimal weights to minimise the variance of the combination forecasts. Clemen (1989), Fildes and Ord (2002), Granger (1989), Greenaway-McGrevy (2022), and Shen et al. (2008, 2011) all used this procedure and found it to be effective in practice. This is because estimating the optimal combination weights can be extremely difficult in practice. While forecast combinations with an equal weighting scheme may be biased, they have the potential to reduce forecast error variance by not depending on projected combination weights based on prediction error second moments (Elliott & Timmermann, 2004). According to Palm and Zellner (1992), the SA forecast combination has many advantages. To begin with, the weights are known and do not need to be estimated—a significant advantage if there is considerable uncertainty regarding the effectiveness of individual forecasts or if the parameters of the model that generates the forecasts are time variable. Second, in many cases, SA forecasts achieve significant reductions in variation and bias by averaging out individual bias (Hibon & Evgeniou, 2005; Wu et al., 2020). Third, it is frequently preferable to the optimal weighting scheme when sample errors and model uncertainty are taken into consideration. Clemen (1989) claimed that this method combines the virtues of robustness, impartiality, and a track record of success in economic and commercial forecasting. In combining forecasts given by two or more models, it is crucial to determine the weights assigned to each model. This simple forecasting combination gives equal weight to each forecast. The combination forecast is provided by:

$$f_{ct} = \sum_{i=1}^{n} w_i \, f_{it} \qquad (6.10)$$

6.6.2. The variance–covariance (VACO) method

The VACO approach was proposed by Bates and Granger (1969). Typically, the linear weights of individual forecasts are calculated in order to minimise the error variance of the combined forecasts that assume unbiasedness for each individual forecast. The VACO combination method principle is illustrated using the case of two forecasting models.

A possible estimator of the combination weight in practice is as follows:

$$w_1 = \frac{\sum_{t=1}^{T} e_{1t}^2}{\sum_{t=1}^{T} e_{1t}^2 + \sum_{t=1}^{T} e_{2t}^2}, \quad w_2 = \frac{\sum_{t=1}^{T} e_{2t}^2}{\sum_{t=1}^{T} e_{1t}^2 + \sum_{t=1}^{T} e_{2t}^2}, \qquad (6.11)$$

Where e_{1t} and e_{2t} are individual forecast errors, and T is the sample.

According to Fritz et al. (1984), the preceding method can simply be extended to have more than two individual forecasts, and the weights can be calculated by:

$$W_i = \frac{\left[\sum_{t=1}^{T} e_{it}^2\right]^{-1}}{\sum_{j=1}^{m}\left[\sum_{t=1}^{T} e_{jt}^2\ \right]-1} \qquad (6.12)$$

As can be seen in Table 6.12, the SA technique generates more accurate forecasts than the VACO technique in 66 percent of cases (4 out of 6). This aligns with previous studies, such as Genre et al. (2013), which found that only a few combination methods outperform SA. However, Shen et al. (2008) found that the VACO method generated more accurate forecasts than the SA techniques. RMSE and MAPE gave the same ranking in two out of six cases, which represents 33 percent of cases. The MAPE and RMSE ranked differently in four out of six cases, which represents 67 percent of cases.

Table 6.12. Forecasting accuracy of combination forecasting method based on RMSE and MAPE, 2017 to 2019

Forecast method	Religious		Business		VFR	
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
SA	0.0643(1)	84.2550(2)	0.0849(1)	15.8125(2)	0.04526(1)	19.0699(1)
VACO	0.0721(2)	26.7801(1)	0.1461(2)	10.4595(1)	0.0855(2)	28.3186(2)

Table 6.13 shows the forecasting performance of all forecasting methods based on MAPE and RMSE. Combined forecasts performed better on average in 66 percent of cases (4 cases out of 6), followed by both time series at 17 percent (on average 1 case out of 6), and the econometric model at 17 percent of cases (on average 1 case out of 6). These results align with the findings of Wong et al. (2007), and Oh and Morzuch (2005), which showed that combining forecasts is not always better than using the best single-model forecasts, but they are always better than using the worst models. However, other research, such as Chen (2011), and Shen et al. (2008), has concluded that combination forecasts are superior to the best individual forecasts.

In this study, RMSE and MAPE gave the same ranking in 29 percent of cases (7 cases out of 24), and different rankings in 71 percent of cases (17 cases out of 24). However, on average, the RMSE and MAPE gave the same ranking in 78 percent of cases (7 cases out of 9) and differed in 22 percent of cases (2 cases out of 9). Li et al. (2005) reviewed forecasting studies and found that the MAPE and

RMSE measures were ranked similarly in 32 of 117 cases, representing 27 percent. Nosier (2012) found that the MAPE and RMSE had the same ranking in 169 out of 220 cases.

Table 6.13. Forecasting accuracy of time series, econometric and combination forecasting methods based on RMSE and MAPE, 2017-2019

Method	Forecast models	Religious		Business		VFR	
		RMSE	MAPE	RMSE	MAPE	RMSE	MAPE
Time series	ARMA	0.034(2)	18.661(3)	0.116(2)	38.971(3)	0.08533(5)	39.80514(6)
	Exponential smoothing model	0.028(1)	16.818(1)	0.1610(5)	44.17944(6)	0.073189(4)	34.27363(5)
	Naive approach	0.067(7)	49.953(7)	0.229(6)	40.9669(4)	0.062504(3)	26.65212(3)
	Average	**0.043(1)**	**28.478(2)**	**0.168(2)**	**41.372(2)**	**0.0736(2)**	**33.576(2)**
Econometric	An ECM	0.0357(3)	17.827(2)	0.142(4)	45.036(7)	0.047(2)	15.806(1)
	VAR	0.0406(4)	22.921(4)	0.399(8)	41.169(5)	0.134(8)	95.897(8)
	ARDL	0.066(6)	26.808(6)	0.302(7)	74.073(8)	0.097(7)	57.472(7)
	Average	**0.047(2)**	**22.519(1)**	**0.2814(3)**	**53.426(3)**	**0.092(3)**	**56.391(3)**
Combined forecasts	SA	0.064(5)	84.255(8)	0.084(1)	15.812(2)	0.045(1)	19.069(2)
	VACO	0.072(8)	26.780(5)	0.146(3)	10.459(1)	0.085(6)	28.3186(4)
	Average	**0.068(3)**	**55.517(3)**	**0.115(1)**	**13.136(1)**	**0.065(1)**	**23.6942(1)**

Source: Author's own calculation using EViews and Excel. *Note:* The ranking is included in parentheses.

6.7. Summary and conclusion

This chapter has evaluated and compared the empirical performance of various forecasting methods across the time period 2017 to 2019. The individual forecasts were generated from three econometric models and three time series models. The SA combination method and the VACO combination method were employed to forecast the growth rate of tourism demand in Saudi Arabia for the three visiting purposes (religious, business and VFR). RMSE and MAPE were used to evaluate the forecasts for each visiting purpose separately.

In time series forecasting, exponential smoothing models were the best models for forecasting religious tourism demand growth rates, and naive-1 model forecasts performed best for VFR tourism demand. Exponential smoothing models and ARMA were the best models for forecasting business tourism demand growth rates. For econometric forecasting, ECM forecast models performed best for all visiting purposes (except MAPE in the business tourism demand growth rate). On average, when comparing time series models to econometrics, the former performs better in 83 percent of cases. Moreover, SA forecasting methods were superior to VACO in generating a forecast-combined method. On average, combination forecast methods outperformed series models and econometric forecast models in 66 percent of cases. However, although combined forecasting methods performed better in most cases, this does not necessarily mean they provide more accurate forecasts than traditional individual forecasting methods in all situations.

On the basis of MAPE alone, econometric models performed better than the time series models and the combined methods in forecasting the growth rate of religious tourism demand, while the combined forecast methods did better in forecasting the growth rate of business and VFR tourism demand. Using the RMSE performance measure, the time series model ranked the best in forecasting the growth rate of religious tourism demand, while combined forecasting did better in forecasting the growth rate of business and VFR tourism demand. When comparing the forecasting of the time series models to the econometric models, it was found that, on average, the RMSE and MAPE ranked the same in four out of six, or 67 percent of cases. However, the MAPE and RMSE ranked differently in two out of six cases, which represented 33 percent. In comparing the forecasting of the time series model, econometric model and combination forecasting methods, RMSE and MAPE had the same ranking on average in 78 percent of cases (7 out of 9), and MAPE and RMSE had different rankings on average in 22 percent of cases (2 out of 9). Song et al. (2008) claimed that this disparity in the measures of forecast errors was evidence of substantial fluctuations among individual prediction errors, since the RMSE is more sensitive to a single poor forecast. Li (2004) stated that discrepancies between MAPE and RMSE are due to various assumptions on the error function forms. Since the actual loss functions are unknown, it would be beneficial to take both measures into account in order to gain a more reliable result.

CHAPTER 7: ASSESSING THE IMPACT OF COVID-19 ON SAUDI ARABIA'S INBOUND TOURISM DEMAND

7.1. Introduction

In this study, sophisticated econometrics methods were developed for forecasting international tourist arrivals from major countries from 2001 to 2019, as discussed in Chapter six. However, no information or method was available to assist in forecasting tourism demand during the uncertain period of the COVID-19 pandemic in 2020 and 2021. Consequently, as part of this study, the impact of the COVID-19 pandemic on tourism demand in Saudi Arabia for the three visiting purposes (religious, business, and VFR) was assessed. Three approaches were used: quantile regression (QR); scenario analysis; and IRFs.

Tourism demand may be affected differently by the COVID-19 variable, which might have different signs (and different significance effects) on tourism demand across varying tourism demand quantiles (low, middle, and high). Therefore, the first objective was to assess the impact of the COVID-19 variable on the disaggregated tourism market by using the quantile regression model. The second objective was to develop a projection of the tourism demand during the pandemic. Econometric approaches (the IRFs) and statistical approaches (scenario analyses) were used to achieve this objective. Whilst IRFs were employed to track the dynamic impact of a shock or change in tourism demand determinants over time, scenario analysis was used to project possible changes in tourism demand determinants to find out the impact of that change on demand. This study introduces a research framework to address the lack of investigation regarding the distinct impacts of a pandemic on various types of tourism demand. The proposed framework aims to analyse and distinguish the effects of COVID-19 on three specific types of tourism demand: religious, business, and VFR. By doing so, the study intends to determine the extent to which each type of tourism demand has been influenced by the pandemic.

The chapter is organised as follows. Section 7.2 provides a discussion on QR and its use in this study. Section 7.3 and Section 7.4 examine the use of scenario analysis and IRF, respectively. Section 7.5 concludes the chapter.

7.2. Quantile regression (QR)

As previously discussed, the COVID-19 pandemic created more serious shocks than previous crises because of long lockdowns and more stringent limitations. To assess its impact on tourism demand, the appropriate methodology had to be chosen. There are benefits to applying the QR technique as an empirical tool. For instance, the likelihood that the impact of the health risk may vary across the level of tourism demand can be disentangled under this approach.

QR is a statistical technique used to determine the relationship between a dependent variable and several independent variables at different points in the conditional distribution of the dependent variable. The conditional distribution of the dependent variable represents the probability distribution of the dependent variable given a specific value of the independent variable(s). The QR approach is a useful tool to capture such asymmetries as it analyses the responses of the dependent variable across the entire conditional distribution (Baur, 2013).

A major limitation of OLS regression models is that they consider only the average relationship between explanatory variables and dependent variables. While QR assists in estimating the conditional median value of the response variable, the linear model just considers the mean value and ignores the variation in the behaviour of selected variables (Sini et al., 2022). Therefore, in this study, the QR estimation approach, which was introduced by Koenker and Bassett Jr (1978), was employed in order to comprehend the dependence structure between variables across the different market stress states. When compared with an OLS estimation, the QR model provides advantages in terms of dealing with heteroscedasticity, presenting a more detailed description of the conditional distribution, being less susceptible to outliers, and providing a comprehensive picture of covariate effects (Barnes & Hughes, 2002; Koenker & Hallock, 2001).

The QR method has been used in a number of tourism studies. This includes Hung et al. (2012), who investigated the determinants of tourism expenditure in Taiwan; Lew and Ng (2012), who assessed visitor expenditure in Hong Kong; Saayman and Saayman (2012), who analysed three sporting events in South Africa; Chen and Chang (2012), who looked at the impact of travel agents on travel expenditure in Taiwan; Lv and Xu (2017), who analysed the impact of corruption on tourism; Kernshi and Waheed (2021), who investigated the relationship between COVID-19 and the total number of inbound tourists in Saudi Arabia in 2020; and Lee and Chen (2022), who examined the effect of COVID-19 on the changing distribution of leisure and tourism industry returns.

In this study, confirmed cases of COVID-19 were used as a proxy from health risks, since the WUPI provides data on a quarterly basis. To estimate quantile models, more data was needed to reach sufficient observations. In Saudi Arabian tourism, monthly data is available for 2020 and 2021. The panel data at the origin country level is crucial in improving our understanding of COVID-19, but it cannot be used for estimation because information on the number of tourists categorised by the purpose of their visit and their country of origin is currently unavailable.

This investigation crucially examined the COVID-19 variable impacts on the changing distributions of tourism demand for the three visiting purposes (religious, business, and VFR) via a QR model using monthly data from January 2020 to December 2021 as time-series data. The reason for choosing this timeframe was to provide evidence of the early impact of COVID-19 on tourism demand following the

WHO declaration on 30 January 2020 that COVID-19 was a global health risk (and characterised as a pandemic in March of that year).

The following hypothesis was formulated:

- ***Hypothesis*** $\boldsymbol{C_1}$: The confirmed cases of COVID-19 variable have a significant effect on religious, business, and VFR tourism demand.

Assaf and Tsionas (2018) argued that slope coefficients at the median of a distribution may differ from those at the lower and higher levels, which is critical when the sample data show significant variability. Consequently, tourism demand may be affected differentially by the COVID-19 variable; that is, COVID-19 may have different signs and/or considerable impacts on demand across various quantiles of demand. This could well be supported by the fact that rapid progress in implementing vaccination programs led to a drop in the number of cases, enhanced traveller confidence, and lessened entrance restrictions in a number of destinations, this leading to an increase in tourism demand. This study sought to examine how COVID-19 affected tourism demand to Saudi Arabia during the high, low, and middle periods of demand. Therefore, a second hypothesis was formulated:

- $\boldsymbol{Hypothesis\ C_2}$: The effect of confirmed cases of COVID-19 on tourism demand varies across different quantiles.

The following section provides the QR model estimates for the nexus between confirmed cases of COVID-19, as a proxy for health risks, and tourism demand.

7.2.1. QR empirical results

Since the focus of this section is on the impact of health risks on tourism demand, this study only examined the impact of health risks on tourism demand for religious, business and VFR visiting purposes. Data for the number of tourists to Saudi Arabia was gathered from MAS in Saudi Arabia and COVID-19 case data was collected from the WHO.

Table 7.1 presents the results of the QR estimation for religious tourism demand. The results are reported for the 20^{th}, 40^{th} 60^{th} and 80^{th} percentiles, based on limited available data. The results of the QR indicate a negative association between health risk and religious tourism in Saudi Arabia. In all quantiles, the coefficients were negative as well as significant.

Table 7.1. Quantile estimations for religious tourism demand, January 2020 to December 2021

Quantile level	Health risk coefficient	Constant	Pseudo R-squared	Adjusted R-squared	Quasi-LR statistic	Ramsey RESET test
20^{th}	-0.6794*** (0.000)	6.7119*** (0.000)	0.2076	0.1715	17.5017 (0.000)	0.1536 (0.695)
40^{th}	-0.6343*** (0.000)	6.3031*** (0.000)	0.3903	0.3626	11.4713 (0.000)	0.1637 (0.685)
60^{th}	-0.5973*** (0.000)	6.814679 (0.000)	0.4583	0.4336	18.6703 (0.000)	0.3884 (0.533)
80^{th}	-0.4904*** (0.008)	7.6208*** (0.000)	0.5207	0.4989	14.486 (0.000)	2.1804 (0.139)
Observations:	24					

Notes: *, **, *** refer to 10%, 5% & 1% significant levels, respectively. The numbers in brackets () are the *p-values*.

While health risks were related to a significant coefficient at the low quantile levels (20^{th}, 40^{th}), they took on a less negative coefficient at the higher quantile levels (60^{th} and 80^{th}). This signifies that health risks reduced the number of religious tourists. In the context of religious tourism demand, in general, the magnitude of the effect kept decreasing from lower to upper quantiles and achieved the highest point at the 20^{th} quantile level (-0.679). This study covered 2020 and 2021 and there are some potential explanations for these relationships. When COVID-19 confirmed cases spread and there were numerous infections in Saudi Arabia, the authorities closed borders, among other measures, to control the spread of the infection and, as a consequence, tourism demand became low.

When countries began controlling the spread of the virus by starting vaccination programs, borders opened for fully vaccinated tourists, hence increasing tourism demand. When the tourism demand was high, the impact of COVID -19 was less than when there were travel restrictions. In the 20^{th} quantile level, the relationship between health risks and religious tourism demand in Saudi Arabia was negative and the coefficient was 0.679, which is significant at a 1 percent level of significance. The pseudo R^2 value ranged from 0.20 to 0.52 in all quantiles, implying that the goodness of fit was appropriate. In terms of adjusted R-squared, the health risk was only explained between 17 and 49 of the variations in total tourist arrivals. The highest was at the 80^{th} quantile, with the health risk explaining 49 variations in total religious tourist arrivals. The Ramsey RESET test showed that the p-value was greater than 5 percent. This indicates that there is no evident non-linearity in the regression equation, and it would be concluded that the model is appropriate.

Table 7.2. Quantile estimations for business tourism demand, January 2020 to December 2021

Quantile level	Health risk coefficient	Constant	Pseudo R-squared	Adjusted R-squared	Quasi-LR statistic	Ramsey RESET test (stability)
$\mathbf{20^{th}}$	-0.1748*** (0.009)	5.4039*** (0.000)	0.2439	0.2096	8.8149 (0.002)	4.3381 (0.032)
$\mathbf{40^{th}}$	-0.1647*** (0.001)	5.0689*** (0.000)	0.2925	0.2604	8.3593 (0.003)	4.6513 (0.031)
$\mathbf{60^{th}}$	-0.1348** (0.010)	5.1088*** (0.000)	0.2836	0.2511	9.1872 (0.002)	2.5083 (0.113)
$\mathbf{80^{th}}$	-0.1118** (0.010)	5.0039*** (0.000)	0.4139	0.3858	13.909 (0.000)	1.6593 (0.197)
Observations:	24					

Notes: *, **, *** refer to 10%, 5% & 1% significant levels, respectively. The numbers in brackets () are the *p-values*. The quantile regression analysis indicates that health risk has a greater impact at lower l and high levels of tourism demand.

Table 7.2 shows the results of the QR estimation for business tourism demand. The results are reported for the 20th, 40th, 60th, and 80th percentiles. The results of the QR indicate that the relationship between health risk and business tourism in Saudi Arabia was negative as well as significant. The effect of health risks decreased from the lower to upper quantiles, reaching the highest point in the 20th quantile (-0. 1748). This means that at the low quantiles, the health risk impact on tourism demand was greater and its impact less at the high quantiles. The primary reason for this negative relationship may relate to the travel restrictions from and to Saudi Arabia and the closing of borders to prevent the spread of the virus.

The magnitude of the negative relationship between health risks and business tourism decreased as a result of the relaxation of travel restrictions and the resumption of flights. The resulted from the decreasing impact of the virus due to different measures and vaccinations. The pseudo R^2 value ranged from 0.24 to 0.41 in all quantiles. This indicates that about 24 to 41 percent of the variation of business tourism demand was expressed by health risks as the explanatory variable, implying that the goodness of fit is appropriate. The Ramsey RESET test showed that the p-value was greater than 5 percent. This indicates that there is no evidence of misspecification and the QR (Median) model was correctly specified.

Table 7.3. Quantile estimations for VFR tourism demand, January 2020 to December 2021

Quantile level	Health risk coefficient	Constant	Pseudo R-squared	Adjusted R-squared	Quasi-LR statistic	Ramsey RESET test (stability)
20^{th}	-0.4584** (0.0435)	5.7904*** (0.000)	0.1413	0.1022	5.3232 (0.021)	5.3029 (0.021)
40^{th}	-0.4033*** (0.002)	5.5504*** (0.000)	0.2461	0.2118	4.8117 (0.028)	6.4972 (0.010)
60^{th}	-0.4111*** (0.004)	5.1224*** (0.000)	0.2155	0.2054	3.1458 (0.0761)	8.4592 (0.003)
80^{th}	-0.2547 (0.130)	5.1680*** (0.000)	0.26391	0.2331	6.0570 (0.013)	1.8809 (0.170)
Observations:	24					

Notes: *, **, *** refer to 10%, 5% & 1% significant levels, respectively. The numbers in brackets () are the *p-values*.

Table 7.3 shows the results of the QR estimation for VFR tourism demand. The negative effect of health risks on VFR tourism demand was apparent in the 20^{th} , 40^{th}, 60^{th} *and* 80^{th} quantiles, and the distribution is significant at the 20^{th}, 40^{th} and 60^{th} quantiles. As with religious and business tourism demand, the highest point was reached in the 20^{th} quantile (0.4584). This result indicates that health risk had a significant and negative effect on VFR tourism at the lower quantiles.

It can be implied that VFR tourism demand was more sensitive to health risks at the low quantiles and less sensitive at high quantiles. Furthermore, religious tourism demand was more sensitive to health risks than other visiting purposes. The response of the dependent variable to the independent variables suggests the heterogeneity of tourism demand in this method. Table 7.3 shows that the adjusted R-squared/pseudo-R2 described the explanatory power of the model. The pseudo R^2 value ranged from 14 to 28 over the quantiles, and the adjusted R-squared ranged between 10 to 23. This indicates that there is a weak relationship between VFR tourism demand and health risk. The result of the Ramsey RESET test shows that the p-value is greater than 5 percent, which indicates that there is no evidence of misspecification and the QR (Median) model was correctly specified. Thus, the model is appropriate.

To validate whether there is a significant difference in the estimates of COVID-19, the Wald test formulated by Koenker and Bassett (1982) was performed for the following null hypothesis: the slope parameters are equal across different quantiles. The null hypothesis was then tested.

Table 7.4. Wald test for the quantile slope equality test and symmetric quantile test

Quantile	Religious Chi-Sq. Statistic (Prob.)	Business Chi-Sq. Statistic (Prob.)	VFR Chi-Sq. Statistic (Prob.)
Quantile slope equality test			
0.2, 0.4	52.33*** (0.004)	78.66 *** (0.006)	64.20** (0.040)
0.4, 0.6	91.32*** (0.003)	56.00*** (0.005)	59.21*** (0.007)
0.6, 0.8	66.00*** (0.005)	40.42* (0.088)	60.30** (0.047)
Symmetric quantiles test			
Wald test	**Religious Chi-Sq. Statistic (Prob)**	**Business Chi-Sq. Statistic (Prob)**	**VFR Chi-Sq. Statistic (Prob)**
	13.91*** (0.017)	35.80*** (0.004)	55.53*** (0.003)

Notes: *, **, *** refer to 10%, 5% & 1% significant levels, respectively. Prob-values reported in parentheses.

Table 7.4 shows that the Wald test results were statistically significant, thus the null hypothesis of slope equality across quantiles was rejected. This finding confirms that the relationship between the dependent variable and explanatory variables differs across quantile values. Therefore, linear models may yield inappropriate results regarding the existence of a relationship between the explanatory and dependent variables. If a relationship does exist, these models may indicate an incorrect conclusion regarding the strength of the relationship.

The results of the test for symmetry between quantiles are also shown in Table 7.4. The null hypothesis for this test was that the distribution is symmetric. The Wald test of symmetric quantiles was statistically significant, which implies that there is significant asymmetry. Thus, the hypothesis of null symmetry between quantiles could be rejected in this case, and asymmetry could be assumed. These findings confirm the heterogeneous impact of the COVID-19 cases variable on tourism demand for all visiting purposes. These results are consistent with Kernshi and Waheed (2021), who presented evidence that the daily growth in total COVID-19 confirmed cases had notable negative impacts on tourism demand, measured by the number of flights to the country. Lee and Chen (2022) concluded that the rate of change in COVID-19 deaths had considerable negative impacts on the changing of distribution returns in the travel and leisure industries at most quantiles. COVID-19 of confirmed cases had a significant and detrimental effect only on the lowest return quantiles.

7.3. Scenario analysis

This section discusses the use of scenario analysis to assess the impact of COVID-19 on international tourism demand in Saudi Arabia. Tourism demand projections during the uncertainty period were conducted using several scenarios, assuming different possible changes in the tourism demand determinants.

The private sector has utilised scenario analysis for the past quarter of a century to manage risk and develop robust strategies in uncertain situations. Scenario analysis is also used in economics, finance, and accounting when managing risk and making investment decisions such as portfolio selection or capital investments (Gunay et al., 2020). Scenario analysis is used to figure out how various events might affect the way a system is working by looking at several possible outcomes. It can be used to consider how a system might act when something unexpected happens. Businesses can use it to assess the benefits and risks of various business decisions. To avoid any form of bias, the scenario analysis may include a variety of potential impacts (Punjabi, 2005). In addition, with scenario analysis, more than one factor can change at the same time, to assess the impact of change in different circumstances. For an analysis of the past, scenario analysis permits the identification of primary driving factors and the comprehension of the effects of these factors on participants.

This study's methodology is consistent with previous studies. For exemple, Page et al. (2012) used two scenarios (no impact and economic crisis) to assess the impacts of a swine flu pandemic on tourism demand in the UK. Ossman and Elsayed (2009) also used a scenario analysis to investigate the impact of the global financial crisis in the second half of 2008 on Egypt's tourism demand. Their study built a baseline scenario to reflect the situation in the absence of the crisis and compared it with the results of other scenarios under a decline in world income by one percent and two percent. Gunay et al. (2020) employed a scenario analysis technique to assess the short-term impacts of the COVID-19 pandemic on the tourism and hospitality industries in Turkey. Their model predicted a total revenue loss for 2020 of USD 1.5 billion and USD 15.2 billion, in the best and worst scenarios respectively. The worst-case scenario involved border closures for four months with no economic recovery. According to their results, the COVID-19 pandemic would be one of Turkey's worst tourism crises, and its losses would surpass those from previous public health crises caused by swine flu, avian Flu, and SARS. Plzáková and Smeral (2022) projected three scenarios in the form of modest optimistic, optimistic, and pessimistic variants based on the state of the economy for 2020, 2021 and 2022.

This study made projections to assess the impact of COVID-19 on the number of international tourists travelling to Saudi Arabia in 2020 and 2021. This was conducted within the scope of three scenarios (and a no change scenario) based on possible changes in the rate of health risks and income (GDP growth in the host and origin countries). Health risks and GDP were chosen because consumer behaviour in travel demand is influenced by a variety of factors, including personal economic, well-being and disposable income, cost fluctuations and perceived health hazards (Lee & Chen, 2011). The GDP of both origin and destination countries was used since an improved economy gives people greater purchasing power to allocate to tourism activities and greater wealth in the host country enables the provision of higher quality services (Marti & Puertas, 2017). The no impact scenario considered the situation in the absence of a pandemic and compared this to the results of the other hypothetical scenarios. The tourism demand model was estimated before the COVID period from 2001 to 2019 and this model was used to do the projections during the COVID-19 period (2020 and 2021).

As indicated above, the explanatory variables used in the scenario analysis were GDP for both origin and destination countries, and health risks. It was assumed that COVID-19 (a health crisis) was exogenous to the economic indicators, but COVID-19 lead to tight restrictions on business and social life, and therefore it is likely to be endogenous as well. The health risk was measured using the WUPI, developed by Ahir et al. (2018, 2020), as explained in Chapter four. Page et al. (2012) measured the impact of the swine flu pandemic by using changes in GDP and CPI. Kocak et al. (2022) used the WUPI and the world discussion about pandemics index (WPDI) to assesses the impact of global pandemic uncertainty and pandemic discourse on tourist arrivals to the US from 1999 to 2020. Karabulut et al. (2020) utilised the WPDI to measure pandemics over the period 1996 to 2018. Ho and Gan (2021) argued that measuring global uncertainties caused by the COVID-19 pandemic using the WUPI assists researchers and policymakers in measuring the socio-economic effects of pandemics.

7.3.1. Scenario analysis outcome and discussion

As noted above, to assess the impact of COVID-19 on tourism demand, three alternative scenarios were projected (minimum, medium, and worst change scenarios). The three scenarios were compared with the no change scenario. The differences between each projection scenario and the no change scenario were used to measure the impact of the pandemic.

7.3.1.1. No change scenario

This scenario assumes that COVID-19 did not occur in 2020 and 2021. Based on data collected from 2001 to 2019, an econometric model was employed to estimate the economic relationship between Saudi Arabian tourism demand and its determinants. Due to this, the demand data (including arrivals, income, health risks, tourism prices, and travel costs) did not include information regarding the COVID-19 pandemic. The next step was to forecast the tourism demand factors under a no impact scenario for 2020 and 2021. To forecast these influencing factors based on historic data from 2001 to 2019, an exponential smoothing approach was used. Research conducted in the past (Song, Witt, & Jensen, 2003; Song, Wong, et al., 2003) has demonstrated that this approach generally produces more accurate forecasts of explanatory variables than other methods based on time series. By substituting these estimated values into an econometric model of the demand relationship for tourism demand, a forecast of tourism demand (visitor arrivals) was then generated for this period. These forecasts were based upon the number of arrivals that would have been expected without COVID-19. As a result, the difference between the forecasts of tourism demand under this scenario and those under other scenarios over 2020 and 2021 would indicate how significant an impact COVID-19 had on tourism demand during this period. Table 7.5 provides the data used in the no change scenario.

Table 7.5. Estimated number of inbound tourists for 2020 and 2021 in the no change scenario

Year	Religious	Business	VFR
2020	8,745,523	1,963,387	2,527,642
2021	9,098,729	1,992,838	2,717,563

7.3.1.2. Minimum change scenario

In this scenario, it was supposed that some restrictions were in effect as a result of COVID-19, but less than in the medium scenario. Health risk values were increased by 8.5 percent in 2020 compared to 2019, then decreased by 3 percent in 2021 compared to 2020. The value of GDP for both countries on average was decreased by 2.5 in 2020 compared to 2019, and increased by 1.5 in 2021, with other variables holding constant. These estimated values were then substituted in the model to generate forecasts of tourism demand (tourist arrivals) for 2020 and 2021**.** Table 7.6 provides the data used in the minimum change scenario. This scenario can be summarised as follows:

GDP ↓2.5 percent in 2020 and ↑1.5 percent in 2021. Health risk ↑8.5 percent in 2020 and ↓3 percent in 2021

Table 7.6. Estimated number of inbound tourists for 2020 and 2021 in the minimum change scenario

Year	Religious	Business	VFR
2020	6,358,998	1,602,792	1,907,904
2021	6,360,203	1,673,428	1,997,704

7.3.1.3. Medium change scenario

In this scenario, health risk values were increased by 17 percent in 2020 compared to 2019, then decreased by 6 percent in 2021 compared to 2020 (this percentage was based on actual data from the WUPI). The value of GDP on average for both countries was decreased by 4.5 in 2020 compared to 2019 and increased by 2.8 in 2021 compared to 2020 (this percentage was based on actual GDP growth date from the World Bank), with other variables holding constant. These estimated values were then substituted in the model to generate forecasts of tourism demand (tourist arrivals) for 2020 and 2021. Table 7.7 provides the data used in the medium change scenario. This scenario can be summarised as follows:

GDP ↓4.5 percent and ↑2.8 percent in 2021. Health risk ↑17 percent in 2020 and ↓6 percent in 2021

Table 7.7. Estimated number of inbound tourists for 2020 and 2021 in the medium change scenario

Year	Religious	Business	VFR
2020	5,962,676	1,432,216	1,716,853
2021	6,023,691	1,580,686	1,811,090

7.3.1.4. Worst change scenario

In this scenario, the demand dropped to zero as borders were closed in 2020 and 2021, as shown in Table 7.8.

Table 7.8. Estimated number of inbound tourists for 2020 and 2021 in worst effect scenario

Year	Religious	Business	VFR
2020	0	0	0
2021	0	0	0

7.3.1.5. Estimating the rate of change in tourism demand

The rate of change in tourism demand was estimated from the base no change scenario. For example, the rate of change in tourism demand as a percentage from the no change scenario to the minimum impact scenario can be measured by: (number of tourist arrivals from no change scenario - number of tourist arrivals from minimum change scenario / number of tourist arrivals from the no change scenario) *100. The results are provided in Table 7.9.

Table 7.9. Comparing the no change scenario with the three other change scenarios for religious, business, and VFR tourism

The scenarios	Religious		Business		VFR	
	2020	2021	2020	2021	2020	2021
Minimum change: GDP ↓2.5 percent and ↑1.5 percent in 2021. Health risks ↑8.5 percent in 2020 and ↓3 percent in 2021.	-27.29%	-30%	-18.35%	-16%	-24.51%	-26.48%
Medium change: GDP ↓4.5 percent **and** ↑2.8 percent in 2021. Health risks ↑17 percent in 2020 and ↓6 percent in 2021	-31.82%	-33.80%	-27%	-21%	-32.07%	-33.35%
Worst change: Borders close	-100%	-100%	-100%	-100%	-100%	-100%

Note: Percentage is the loss of tourism arrivals.

As shown in Table 7.9, in the minimum change scenario, the number of religious tourists decreased by 27 percent in 2020 and 30 percent in 2021, compared to the number in the no change scenario. In medium change scenario, the number of religious tourists decreased by 31.82 percent and 33.80 percent in 2020 and 2021 respectively. This reflects the huge impact of government restrictions. In the worst change scenario, the country completely lost its tourism demand for all visiting purposes as border closures and restricted travel between countries were imposed.

According Prasetio et al. (2022), the high number of COVID-19 cases has hurt religious tourism in Iraq's holy cities. Nasir et al. (2020) also found COVID-19 decreased the number of religious tourists visiting the Sunan Giri Tomb in Indonesia. In particular, the virus has caused a reduction in revenue from religious tourists, a decrease in religious tourism-related jobs and activities, and a decline in part-time employment and service work related to religious tourism.

For business tourism, in the minimum change scenario, the number of tourists decreased by 18.35 percent in 2020 and 16 percent in 2021, compared to the number in the no change scenario. In the medium change scenario, the number of business tourists decreased by 27 percent and 21 percent in 2020 and 2021 respectively. Again, this reflects the huge impact of government restrictions, which impacted tourism demand for all visiting purposes.

Rittichainuwat et al. (2020) found that the business travel industry in Thailand had recovered quickly post-COVID-19, largely due to marketing strategies to boost tourist confidence.

For VFR tourism in the minimum change scenario, the number of tourists decreased by 24.51 percent in 2020 and 26.48 percent in 2021, compared to the number in the no change scenario. In the medium change scenario, VFR tourist numbers decreased by 32.07 and 33.35 percent in 2020 and 2021 respectively.

Ma et al. (2021) pointed out that during the SARS pandemic, WHO advised individuals to cancel their trips, but VFR travel continued for non-essential purposes. The authors linked their findings to statistics from the Australian Bureau of Statistics on international departures, which indicated that the decline in travel during the SARS pandemic was lower for VFR travellers than for business and holiday travellers. In the pandemic period, tourists preferred to travel short distances (closer to home) instead of using public transportation, to avoid crowded areas. Earlier studies indicate that VFR tourism performs well in economic downturns (Backer, 2012). VFR has been recognised as an appropriate first-mover segment of the tourism market post crises and disasters (Backer & Ritchie, 2017).

The results indicate that business tourism demand was affected the least by COVID-19 and religious tourism the most. It is worth noting that religious and VFR tourism decreased in 2021 more than in 2020 in all three scenarios, although the border was closed for most of 2020. This may be because the pandemic did not affect the number of tourists until March 2020, leading to an increase in the total number of tourists in 2020 compared to 2021, despite Saudi Arabia reopening its borders from July 2021 to fully vaccinate inbound tourists.

The Figures 7.1, 7.2 and 7.3 represent the forecasting methods and scenarios for the three kinds of tourism purposes.

Figure 7.1. Projection of religious tourism demand under the three scenarios for 2020 and 2021

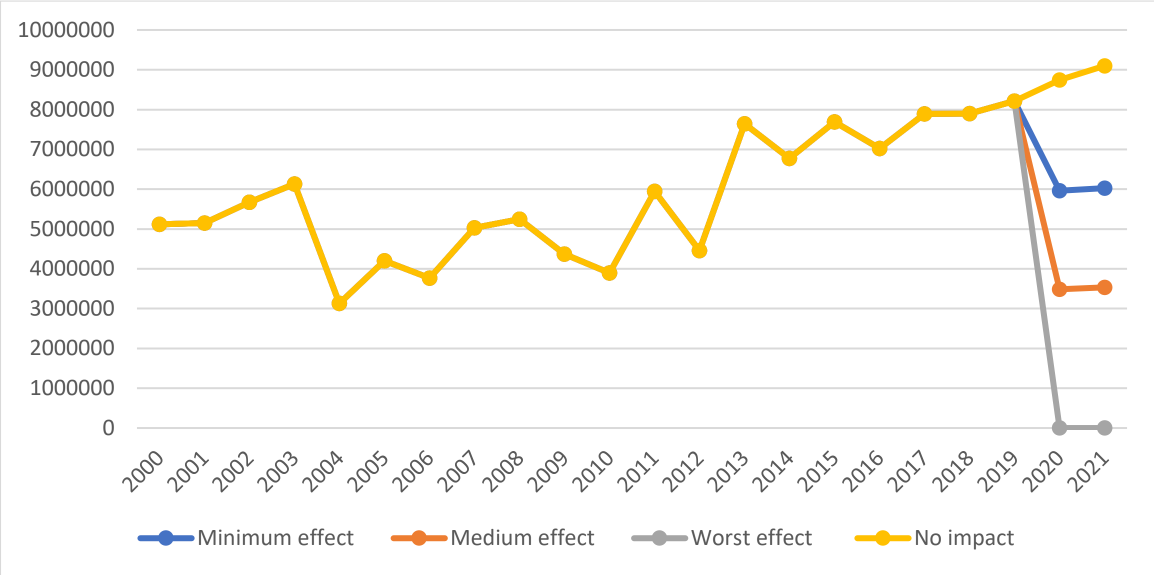


Figure 7.2. Projection of business tourism demand under the three scenarios for 2020 and 2021

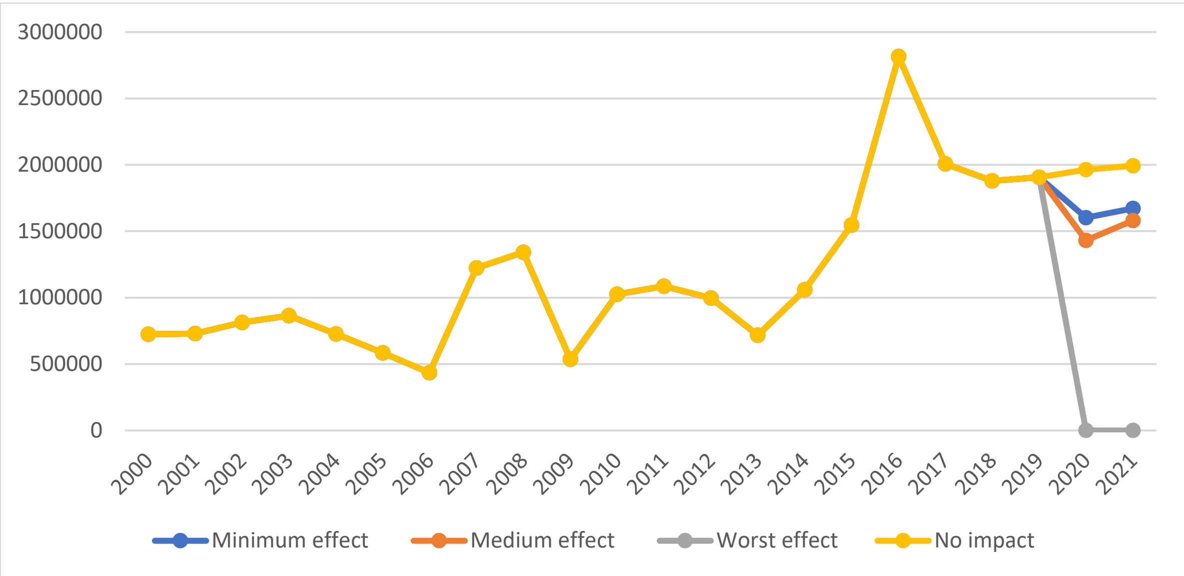
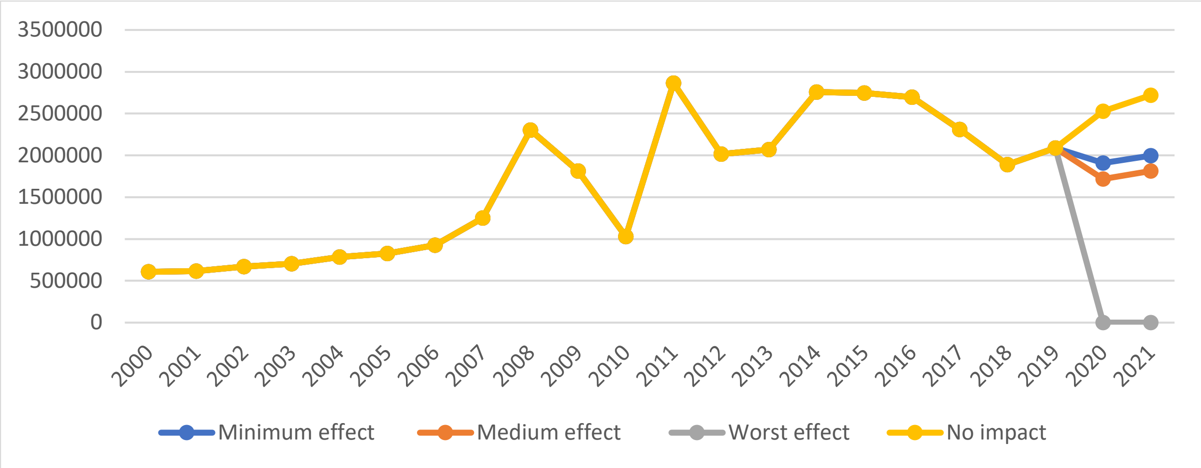


Figure 7.3. Projection of VAR tourism demand under the three scenarios for 2020 and 2021



The results of the estimates show that the decrease in expected income and the increase in health risks led to a decrease in the number of tourists at different rates.

7.4. Impulse response function (IRF)

Whilst scenario analysis looks at the possible change in health risk and income of tourism demand, Impulse Response Function (IRF) significant task in empirical economics is to track the impacts of a shock on the variable(s) of interest. The IRF is used in empirical economics to track the impacts of a shock on the variable(s) of interest. It is also a valuable tool for investigating the impact of a simulated shock using a model built on historical data (Kuok et al., 2022). In this study, IRFs were employed to track the dynamic impact of a shock or change in tourism demand determinants over time. In particular, IRFs were used to examine the variable time path (e.g. tourist arrivals) caused by a shock given by other variables (health risks and income). The future responsiveness of tourism demand to these important variables could then be assessed. The entire dynamic process, from the first shock to the long-term stable state of the variable, could be observed and understood.

The IRF describes the magnitude and direction of the relationship between the variables and illustrates how the variables interact when one standard deviation shock (innovation) is imputed in each of the error terms. Using IRF estimation models, this study aimed to demonstrate the direction and marginal influence of health risks and GDP on Saudi Arabia's tourism demand over the next decade. The IRF examines the reaction of the dependent variable in the VAR model to shocks within the error limit. These functions represent the response of system variables to shocks. The IRF shows the effect of the shock by one standard deviation of one of the variables.

IRF analysis has attracted considerable attention in recent tourism demand studies and is crucial for tourism practitioners (Song & Li, 2008) and policymakers (Hailemariam & Ivanovski, 2021; Song & Witt, 2006). Araña and León (2008), Frey et al. (2007), Kožić et al. (2019), and Berrittella et al. (2006)

have assessed the influence of terrorist attacks and natural disasters on tourism demand. Blake et al. (2003) estimated the effects of foot and mouth disease on tourism and the overall economy of the UK. Hamilton and Tol (2007) assessed the impact of climate change on tourism in Germany, the UK and Ireland. Pambudi et al. (2009) analysed the economic effect of the Bali bombing. Sheldon and Dwyer (2010), Smeral (2010), Song and Lin (2010), and Yang and Chen (2009) investigated the implications of Taiwan's SARS epidemic on tourism.

Torraleja et al. (2009) used the IRF to determine the degree of interdependence between the various tourism markets, based on an examination of the evolution of the relationships between Spain's major tourist receiving centres. Daniel and Rodrigues (2012) employed the IRF to assess how international tourism demand for Portugal responds to shocks in some of its key determinants, such as income, the cost of living in Portugal, and the cost of living in Spain (as a competing market with Portugal). Hailemariam and Ivanovski (2021) used the IRF to determine the endogenously connected relationship between global economic policy uncertainty and demand for US tourism net export spending.

As already discussed, the COVID-19 pandemic caused significant changes in consumer behaviour and it is predicted that these changes will last long after the end of the pandemic (Andersen et al., 2020; Ceylan et al., 2020). Therefore, this study used IRFs to trace the marginal effects of a one-time shock concerning one of the variables (a sudden outbreak of a global health pandemic) on the current and future values of other endogenous variables (international religious, business and VFR tourism demand).

7.4.1. The impulse response function and econometric model development and estimation

This study estimated VAR with data on the number of tourists based on purpose of visit, health risks and the GDP for origin and destination countries, and then IRFs were computed. The model's specification was for ten years, over annual data spanning 2001 to 2019. The IRFs enabled statements to be made about the dynamic relationship between health risk and tourism demand. The empirical results discussed in this section should be interpreted as representing the impact of a particular disease, COVID-19, on tourism demand.

The variables in the VAR were confirmed as stationary based on standard unit root tests. To determine the optimal lag selection, AIC and Bayesian information criteria (BIC) were employed. These indicated two lags for the models. The Cholesky decomposition was used to compute IRFs.

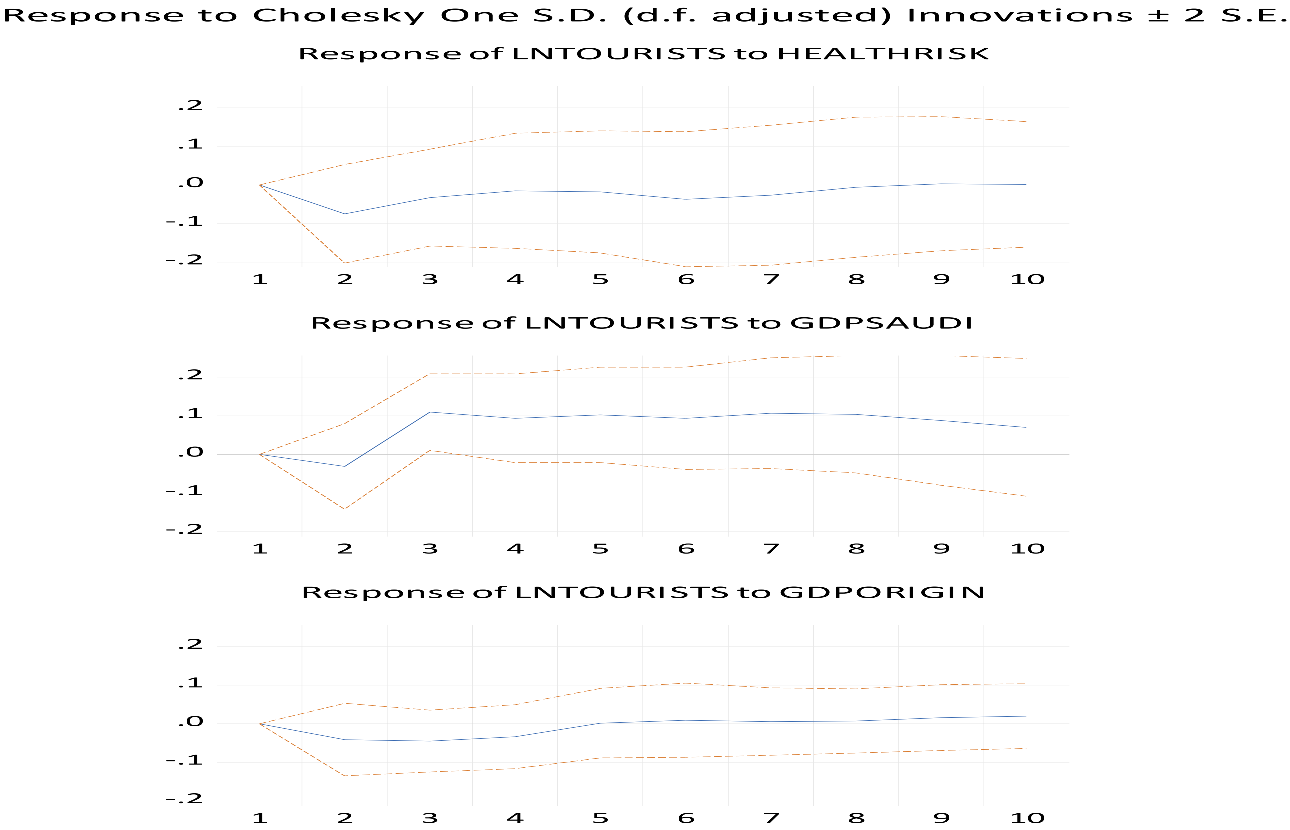
7.4.1.1 The impulse response in religious tourism demand

Figure 7.4 and Table 7.10 show that the results of the health risk shocks had a significant negative effect on Saudi religious tourist arrivals. The number of religious tourist arrivals to Saudi Arabia in response to the health risk shock decreased until year two. From year two, the number of tourist arrivals gradually increased until year eight. From year eight, the numbers were back to the pre-shock level. Clearly, the

COVID-19 pandemic impacted the tourism sector as it was widespread globally, unlike other epidemics confined to specific countries. The impact also depended on the degree of uncertainty induced by the pandemic event and its severity. In this respect, the results of this study show that higher uncertainty and severity were associated with the deepest falls in tourist arrival numbers. These results may help researchers and practitioners understand the future dynamics of the COVID-19 impact.

In the third year of the pandemic, in 2022, Saudi Arabia received one million international and domestic pilgrims, including 850,000 from abroad, which came after two years of drastically curtailed numbers due to the pandemic.

Figure 7.4. Impulse response functions for religious tourism



Note: The solid blue line represents the estimated effect of a one standard deviation shock in the endogenous variable on the other variables in the model. The vertical axis shows the estimated influence, while the horizontal axis represents the number of years. The dotted red lines represent the 95% confidence level.

Table 7.10. Impulse response functions for religious tourism

Period	HEALTH RISK	GDP SAUDI	GDP ORIGIN
1	0.0000 (0.000)	0.000 (0.000)	0.000 (0.000)
2	-0.074 (0.063)	-0.031 (0.055)	-0.041 (0.046)
3	-0.032 (0.062)	0.109 (0.049)	-0.044 (0.040)
4	-0.015 (0.074)	0.093 (0.057)	-0.033 (0.041)
5	-0.018 (0.079)	0.102 (0.061)	0.001 (0.045)
6	-0.037 (0.087)	0.093 (0.066)	0.009 (0.047)
7	-0.026 (0.090)	0.106 (0.071)	0.005 (0.043)
8	-0.006 (0.090)	0.103 (0.07596)	0.007 (0.041)
9	0.002 (0.086)	0.087 (0.083)	0.015 (0.042)
10	0.001 (0.081)	0.069 (0.089)	0.0198 (0.041)

The results of the IRF analysis for Saudi income (GDP SAUDI) show that the shock in this variable had a negative response for two periods and then a positive effect after period two. In fact, Saudi income reached a low point in the first two years after the shock. According to estimates from the GaStat (2020), the GDP of Saudi Arabia had a negative real growth rate of 4.1 percent in 2020 compared to 2019. This negative growth arose primarily from the contraction in the oil sector by 6.7 percent, in addition to a negative growth rate of 2.3 percent reported in the non-oil sector. The private sector decreased by 3.1 percent, and the government sector reported a negative growth rate of 0.5 percent. The Saudi economy has quickly recovered from the negative impacts of the coronavirus pandemic, as the country reported an annual growth rate of 1.8 percent in the second quarter of 2021. Kirson et al. (2022), and Pragyan et al. (2022) indicated that COVID-19 vaccinations had a positive significant influence on economic activity.

The third quarter financial figures also indicated signs of improvement, with total revenues of SR 243.3 billion (USD 64.8 billion) and total expenditure of SR 236.6 billion, resulting in a surplus of SR 6.6 billion for the first time since 2019. Brent crude oil market prices averaged USD 74 per barrel in September 2021 and more than USD 80 per barrel in October 2021, as a result of lifted international travel and other restrictions on mobility. In addition to the contribution of oil income to the budget surplus in the third quarter, non-oil revenues contributed considerably to the surplus by registering a 33 percent raise over the same time in 2020, reaching SR 299.5 billion.

A strong economy can draw tourists and help them build trust in a country's health system. Aronica et al. (2022) sought to predict the future of the tourism industry by analysing the effects of pandemics on tourist arrivals. They concluded that pandemics have a long-term negative impact on tourism, particularly in underdeveloped and emerging countries. A wide range of economic factors influence the impact of pandemics, including general health system performance, the intensity of the shock, and the uncertainty generated by the pandemic occurrence.

The income shocks of the origin countries led to a notably negative effect on religious tourism demand lasting four periods. After that, there was a positive and significant response to shocks from the income of the origin countries. The COVID-19 pandemic led to significant job losses and increased unemployment (Bundervoet et al., 2022; Carli, 2020). As middle and low-income countries are the main tourism market of Saudi religious tourism demand, the shock impacted their ability to travel.

7.4.1.2 The impulse response in business tourism demand

Business tourist travel responses were tiny but significant and negative to the shock in their income (LNGDPI) [10], which remained consistent for close to two periods. After period two, the response was positive. This indicates that business tourists were less sensitive to the shock in their income than religious tourists, since business tourism demand decreased only a small amount in the year of the shock and increased in the second year. This reflects the ability of business tourism to recover.

Business tourism's response to the shock of Saudi Arabia's income was almost the same as the response of religious tourism, but with a much long decline period (religious tourism took two periods in the negative, while business tourism took four periods). Figure 7.5 and Table 7.11 show that, unlike religious tourism, business tourism seemed to be less affected by the health risk (pandemic) shock as the tourist arrivals declined in the first two years after the outbreak of the pandemic, and then the number of tourist arrivals grew to reach a positive response.

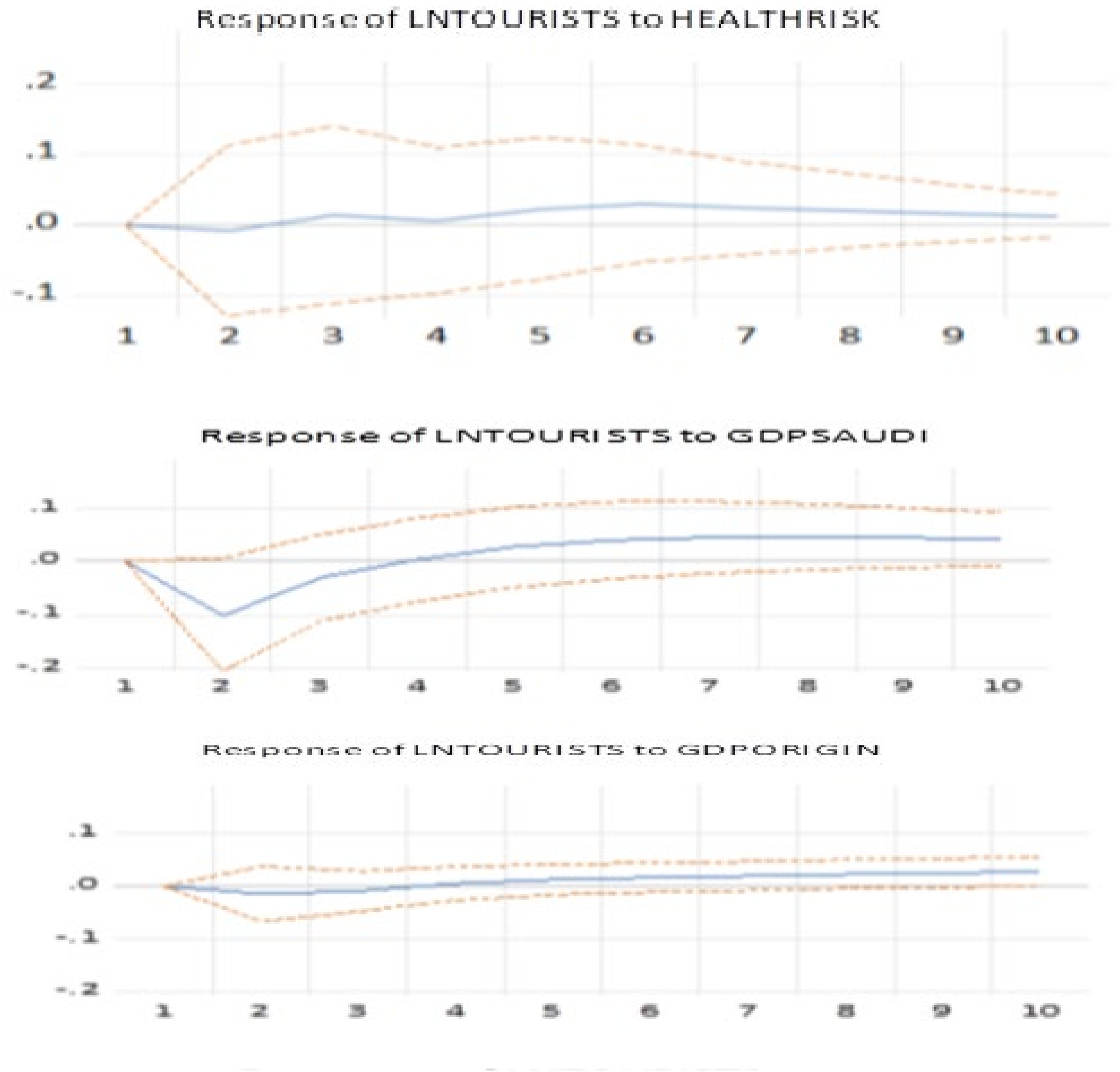
Business tourists are likely to be crisis resistant. Hajibaba et al. (2015) argued that crisis-resistant tourists also have high spending power and are highly targetable since their crisis resilience generally reduces travel cancellations. Crisis-resistant tourists are a desirable niche market for travel suppliers, brokers, and destinations.

Nonetheless, Zoom meetings will still exist post COVID-19, posing a potential challenge for business travel. According to statistics from the business intelligence company, Morning Consult, the proportion of regular business travellers who claim they will never travel again for business increased from 39 percent in October 2021 to 42 percent in February 2022. Using a qualitative research approach, Kuofie

[10] Ln: considers the logarithm of the GDP per capita in the origin (i)and the Saudi (j)

and Muhammad (2021) found that people will continue to work from home, using more video conferences and travelling less for business.

Figure 7.5. Impulse response functions for business tourism



Note: The solid blue line represents the estimated effect of a one standard deviation shock in the endogenous variable on the other variables in the model. The vertical axis shows the estimated influence, while the horizontal axis represents the number of years. The dotted red lines represent the 95% confidence level.

Table 7.11. Impulse response functions for business tourism

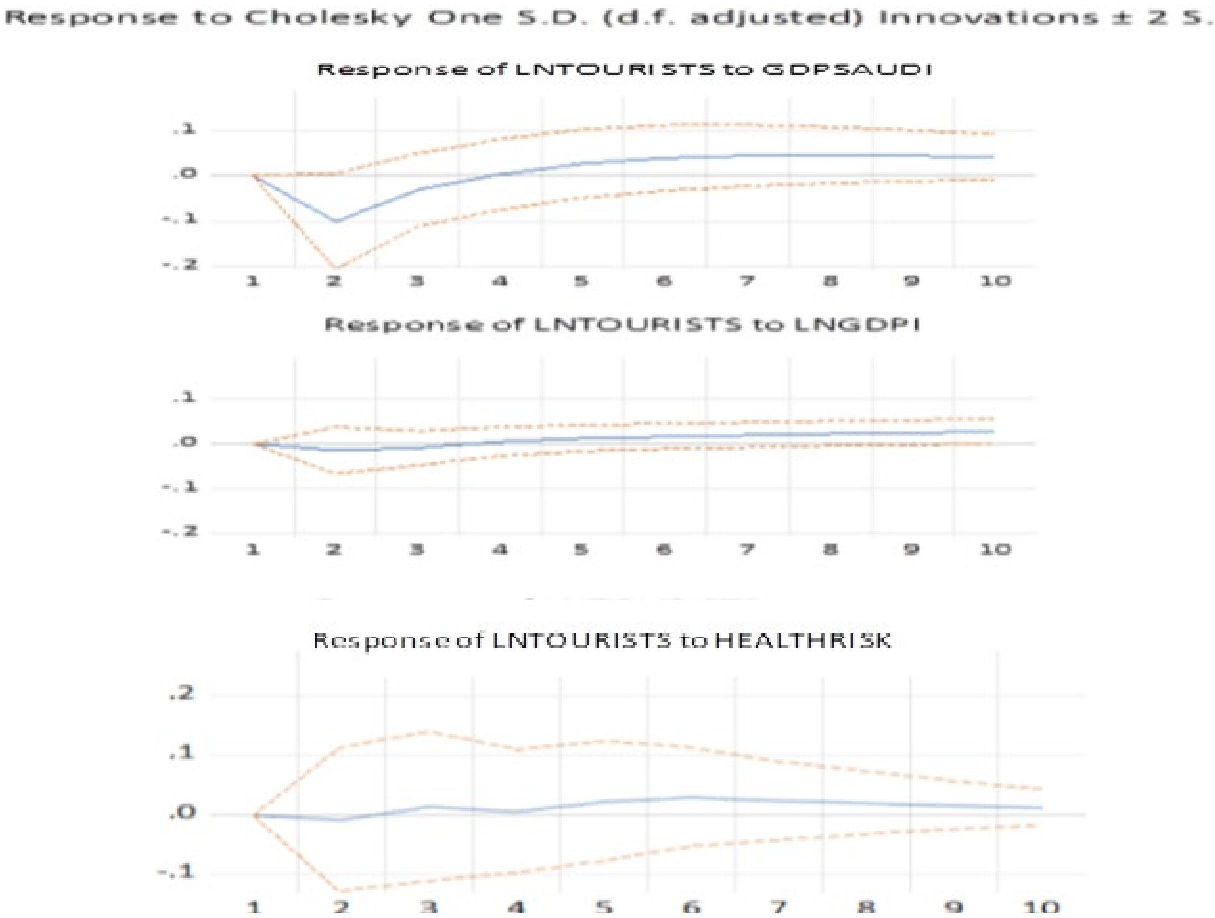
Period	LNGDPI	GDPSAUDI	HERISK
1	0.0000 (0.000)	0.000 (0.000)	0.000 (0.000)
2	-0.015 (0.024)	-0.055 (0.038)	0.056 (0.056)
3	-0.004 (0.016)	-0.011 (0.027)	0.0316 (0.051)
4	0.010 (0.014)	-0.016 (0.030)	0.0141 (0.041)
5	0.018 (0.013)	0.009 (0.032)	0.001 (0.041)
6	0.022 (0.013)	0.021 (0.030)	0.012 (0.029)
7	0.025 (0.013)	0.029 (0.026)	0.017 (0.021)
8	0.027 (0.013)	0.013 (0.019)	0.021 (0.011)
9	0.028 (0.013)	0.030 (0.026)	0.022 (0.014)
10	0.029 (0.013)	0.029 (0.022)	0.021 (0.0128)

7.4.1.3 The impulse response in VFR tourism

Figure 7.6 and Table 7.12 show the IRFs for the VFR tourist arrivals response to shocks in each of the three variables (origin country income, Saudi income, and health risks). The results show that health shocks had a tiny significant negative effect on VFR tourism demand for just one period. The effects of the health shock became positive and significant from period three. VFR tourism demand showed a negative and significant response to shocks in Saudi income (GDPj). The effects were present for almost three periods, before an increase in the number of VFR tourists and a positive response to the shock in Saudi Arabia from period four.

The results show that the origin countries' income shocks had a significant negative effect on the VFR tourism demand for one period, but these effects rapidly became positive and significant in period two. Dube-Xaba (2021) argued that VFR tourists will be more confident to engage in tourism-related activities with their friends and families post COVID-19 because they will be aware of the impact of the pandemic in their friends' and families' areas of residence. According to the Koç (2021), demand for VFR tourism increased after the pandemic, as people were seeking to escape to unknown destinations. Zheng et al. (2021) argued that VFR travel is the safest form of travel for tourists who want to be with their families in times of crisis or just shortly after. During the pandemic, the demand for VFR travel and the preference for relatives' and friends' homes as accommodation increased dramatically.

Figure 7.6. Impulse response functions for VFR tourism



Note: The solid blue line represents the estimated effect of a one standard deviation shock in the endogenous variable on the other variables in the model. The vertical axis shows the estimated influence, while the horizontal axis represents the number of years. The dotted red lines represent the 95% confidence level.

Table 7.12. Impulse response functions for VFR tourism

Period	LNGDPJ	LNGDPI	HERISK
1	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
2	-0.100 (0.053)	-0.014 (0.026)	-0.007 (0.060)
3	-0.030 (0.040)	-0.008 (0.019)	0.0140 (0.062)
4	0.003 (0.039)	0.0058 (0.016)	0.0060 (0.051)
5	0.027 (0.038)	0.0132 (0.014)	0.022 (0.049)
6	0.039 (0.034)	0.016 (0.013)	0.030 (0.041)
7	0.0452 (0.0341)	0.0198 (0.013)	0.022 (0.032)
8	0.046 (0.031)	0.0230 (0.013)	0.019 (0.026)
9	0.044 (0.028)	0.025 (0.013)	0.015 (0.020)
10	0.041 (0.025)	0.027 (0.013)	0.010 (0.015)

To sum up this chapter the pandemic's impact on the tourism industry goes beyond border closures and travel bans. Understanding the situation requires considering various factors and nuances:

- Changes in consumer behavior and confidence have influenced travel decisions. Fear of the virus, financial constraints, and shifting priorities all play a role.

- Governments' diverse responses to the pandemic, ranging from strict measures to more relaxed approaches, have significant implications for the tourism sector.

- Economic aftermaths, such as job losses and income changes, affect tourism demand, impacting people's ability to travel.

- The pandemic has led to a shift in travel preferences, with a notable rise in domestic tourism and alternative destinations.

- Technology and digital platforms have played a crucial role in mitigating the pandemic's impact. Virtual experiences, remote work opportunities, and online booking platforms have facilitated adaptation in the industry.

Considering these factors will lead to a more comprehensive understanding of the pandemic's impact on tourism. This understanding can guide effective strategies for recovery and adaptation.

7.5. Conclusion

The tourism industry is one of the most sensitive to crises. The COVID-19 pandemic was one of the greatest health crises the world has ever faced. This chapter examined and assessed the impact of a health risk (COVID-19) on Saudi Arabia's religious, business, and VFR tourism demand. The WUPI data was used for scenario analyses and IRFs and confirmed COVID-19 case numbers were used in QR to measure the health risk. The research determined that the outbreak of COVID-19 had a significant and adverse effect on Saudi Arabia’s tourism industry, as travel restrictions and bans were imposed by governments around the world. COVID-19 vaccine programs contributed to a slight recovery in 2021.

The three techniques outlined in this chapter confirmed that religious tourism was the most affected by the pandemic, taking more time to recover than business tourism. The results of quantile slope equality tests and symmetric quantile tests confirmed that the relationship between the dependent variable and explanatory variables varied across quantile values.

CHAPTER 8: CONCLUSIONS AND RECOMMENDATIONS

8.1. Introduction

This chapter concludes the thesis with an outline of the key findings related to the study research aims and questions. It presents the theoretical and empirical findings as well as their related policy implications. The chapter also includes a discussion of the study's limitations and some recommendations for future research to continue the work presented in this thesis.

8.2. Overview of the research study

The main aim of this study was to model and forecast tourism demand for three visiting purpose types (religious, business, and VFR) to assist in understanding push and pull factors in tourism, and to predict future tourism demand to support planning and investment. In addition, the study sought to assess the impact of COVID-19 on Saudi inbound tourism demand across the same three visiting purpose types.

To model tourism demand, the gravity model was employed because this type of model is much more diverse in terms of determining factors when evaluating tourism demand. This is important because there is a wide variety of economic and non-economic factors that can become statistically significant when determining the tourism demand of international tourists. Demand theory, by contrast, is primarily focused on income and prices or exchange rates as determinants for demand, which do not sufficiently explain tourism demand.

To investigate the factors that impact international tourist arrivals in Saudi Arabia, based on disaggregate international tourism demand, three models were constructed for each purpose of visit type (religious, business, and VFR). In addition, an expatriate/immigrant model was used. As the data sample for expatriate workers was only available from eight origin countries, this data was estimated separately for both aggregated and disaggregated tourism demand models. To compare the different responses to the determinants of tourism demand between aggregate and disaggregate, this study also developed models for the total number of tourist arrivals, including all the variables.

The panel GMM model method was used to estimate religious tourism demand because the time-series data was smaller than the cross-sectional data. Saudi Arabia is a unique destination for all Muslim people worldwide and religious tourism is the country's major tourism market. The panel ARDL model method was used in business, VFR, the total number of inbound tourist arrivals, and expatriate/immigrant models because the time-series data was larger than the cross-sectional data. The panel GMM and panel ARDL model methods were both employed in this study as they are appropriate when the variables are stationary at the level I (0) or I(1) or a mix of I(0) and I(1), thus avoiding the problem of spurious regression. Panel regression was also estimated for comparison purposes.

The panel unit root tests were conducted to identify the order of integration of the variables. The results concluded that the variables were a combination of I (1) and I(0). To examine the existence of a long-run relationship between the research variables, Kao and Pedroni cointegration tests were used. According to the results, the null hypothesis of no cointegration could be rejected and thus there was a cointegration relationship between tourist arrivals and explanatory factors in the various models. To generate a forecast of religious, business, and VFR tourism demand growth rates, two methods were used: the time series model and the econometric model. To assess the forecasting accuracy, a forecasting method that combined both time series models and econometric models was also used. To determine the forecasting accuracy, MAPE and RMSE measures were used.

Since the tourism sector has experienced a sharp decline since the beginning of the COVID-19 pandemic, the current study attempted to assess the impact of this crisis on disaggregated tourism in Saudi Arabia by using QR, scenario analysis and IRFs. The next section provides a summary of the findings presented in this thesis.

8.3. Summary of empirical analysis

This section presents a summary of the findings against the research questions discussed in Chapter one.

8.3.1. Addressing objective one: Developing holistic models of factors that affect tourism demand.

Chapter five presented the factors identified as affecting international tourism demand for religious, business, and VFR tourists. Since prosperity is gaining a significant amount of attention as a crucial aspect of sustainability and it is a key theme in Saudi Arabia's Vision 2030 for developing tourism demand, this study investigated how prosperity and other factors related to the destination affect tourism demand. Prosperity includes not only the economic component but also the welfare, social reputation, environmental sustainability, quality of life, happiness, peace, and political stability of the destination. This may be the first study to explore these factors at the level of one destination, as the literature is very focused on economic factors alone. Disaggregate and aggregate models were also developed to gain more insights into the issue.

The most significant determinants of tourism inflows to Saudi Arabia were identified as: the income of both origin and destination countries, the cost of living in the destination, travel costs, capital investment in the tourism sector, FDI, trade openness, word-of-mouth, expatriate workers, Saudi international students, political risks, human rights, global health risks, relative temperature, and destination prosperity. To answer the research questions this thesis developed more holistic models for economic factors and selected non-economic factors that impacted disaggregated tourist flows to Saudi Arabia by the purpose of visit (religion, business, VFR) over the period 2000 to 2019.

The first objective of this study was to develop more holistic models for economic and selected non-economic factors to identify their impact on the total number, religious, business, and VFR tourist flows to Saudi Arabia. Several hypotheses were developed to meet this objective, as shown in Table 8.1.

The religious tourism demand models were empirically tested for 21 countries, for the period 2000 to 2019, using the first difference GMM estimation method. The GMM estimator allows for the inclusion of past tourism demand as an explanatory variable of the model. It measures the habit of repeat visits and/or word-of-mouth effects. The results presented in Table 8.1 show that the lagged dependent variable significantly affects religious tourism demand. This suggests that if individuals are satisfied with a destination, they may be more likely to return and share their positive experiences with others. This supported the hypothesis that there is a positive impact of the lagged dependent variable on religious tourism demand flow in Saudi Arabia.

The income of both destination and origin countries, capital investment in the tourism sector in the destination country, sharing a common religion, expatriate workers, enhancing human rights, and destination prosperity, significantly and positively impacted religious tourism demand. Whereas the cost of living in the destination, travel costs, political risks, sharing a common language and relative temperature significantly and negatively affected religious tourism demand. Religious tourism demand was very sensitive to the income of the destination country, tourism price, political risks, and expatriate worker factors. Religious tourism is primarily described in the early literature as a spiritual phenomenon (for example (Norman, 2004; Rinschede, 1992) and does not appear to be linked to income. Consequently, the current study contributes significantly to the literature on religious tourism demand.

Moreover, this research found a negative relationship between the price and demand for religious tourism. This contrasts with the results of the only other study (Shaheen, 2019) that has examined the relationship between tourism price and religious tourism demand, which found a positive relationship between the price and demand for religious tourism. This current study contributes significantly to the literature on religious tourism demand since it is the first to empirically examine the impact of both economic and non-economic factors on religious tourism demand.

The business tourism demand model was empirically tested for 11 countries, for the period 2000 to 2019, using the ARDL estimation method. The results show that the income of both destination and origin countries, capital investment in the tourism sector in the destination country, trade openness, expatriate workers, enhancing human rights, and destination prosperity, significantly and positively affected business tourism demand. Whereas the cost of living in the destination, travel costs, political risks, and global health risks, significantly and negatively impacted business tourism demand. Business tourism demand was very sensitive to the income of the destination country, trade openness, enhancement in human rights, and expatriate worker factors.

This study failed to find any significant association between FDI and business tourism demand, while some scholars confirmed the significant positive effect of FDI (Gholipour & Foroughi, 2019, 2020; Gholipour, Tajaddini, et al., 2021; Kulendran & Witt, 2003a; Selvanathan et al., 2012). Importantly, this current study provides evidence of the impact of a range of factors on business tourism demand (capital investment in the tourism sector in the destination country, expatriate workers in the destination, enhancing human rights, destination prosperity, and global health risks). In addition, it found that the sensitivity of business tourists to travel costs may be because most of the business tourists come from developing countries such as India and Pakistan.

The VFR tourism demand model was empirically tested for 15 countries, for the period 2000 to 2019, using the ARDL estimation method. The results show that the income of both destination and origin countries, capital investment in the tourism sector in the destination country, Saudi students studying overseas, and destination prosperity, significantly and positively affected VFR tourism demand. In contrast, visa restrictions, travel costs, political risks, and expatriate workers, significantly and negatively affected VFR tourism demand. VFR tourism demand was very sensitive to the income of the destination country, capital investment in the tourism sector in the destination country, and visa restrictions. This estimation uncovered some important findings. Firstly, it found no evidence for the positive impact of expatriate workers in the destination on VFR tourism demand, nor a significant impact of tourism prices. Secondly, capital investment in the tourism sector in the destination country, enhancing human rights, students studying overseas, and destination prosperity, had a positive impact on VFR tourism demand.

The aggregate tourism demand model was empirically tested for 14 countries, for the period 2000 to 2019, using the ARDL estimation method. The results show that the income of both destination and origin countries, capital investment in the tourism sector in the destination country, enhancing human rights, FDI, Saudi students studying overseas, expatriate workers, relative temperature, and destination prosperity, significantly and positively impacted aggregated tourism demand. In contrast, travel costs, tourism prices, visa restrictions, political risks, and global health risks, significantly and negatively affected aggregated tourism demand. Aggregated tourism demand was very sensitive to the income of the destination country, capital investment in the tourism sector in the destination country, political risks, expatriate workers, and visa restrictions.

The expatriate worker tourism demand model was empirically tested for eight countries, for the period 2000 to 2019, using the ARDL estimation method. The results show that the income of the destination and origin countries positively affected all tourism demand models. Travel cost significantly impacted tourism demand in the models. Business tourism demand in this sample was more sensitive to travel cost than other types of tourism demand under investigation. The expatriate worker factor was positive and significant in explaining international tourism demand to Saudi Arabia as expected in aggregate, business and religious tourism, but had a negative and significant impact on VFR tourism demand. The dummy variable for the Hajj incident in 2015 had a negative but non-significant impact on religious tourism demand flow in Saudi Arabia.

8.3.2. Addressing objective two: Identify the importance of factors affecting international tourism demand at aggregate and disaggregate levels.

The second objective of this study was to identify the importance of economic and select non-economic factors on international tourism demand at aggregate and disaggregate levels, and whether these varied based on visiting purposes. Again, several hypotheses were developed to meet this objective, as shown in Table 8.1. Overall, the estimated coefficients were in line with the theoretical expectations regarding their sign and the magnitude of the effect.

The income of the destination country was identified as the most significant determinant of tourism inflows to Saudi Arabia for all tourism demand models. Religious and total tourism demand recorded the highest sensitivity to the income of the origin country. Moreover, the regression results indicated that arrivals to Saudi Arabia for all models of tourism demand were sensitive to the income of the origin countries and the sign was positive, as expected, and less than 1. This indicates that tourism to Saudi Arabia is considered a ‘normal good’ and that an increase in income in the origin country will lead to a relative increase in tourism to Saudi Arabia. The hypothesis that there is a positive relationship between the income of the origin and destination countries, and tourism demand in Saudi Arabia could not be rejected. The income of the origin country was important for all tourists, but it was more important for VFR tourism demand.

The cost of living at the destination and cost of travel were significant in all tourism demand models, except for the VFR model, in which the cost of living at the destination was not significant. This supports the hypothesis that there is a negative and significant impact of travel cost and cost of living at the destination on tourism demand flow in Saudi Arabia. Religious tourism demand was more sensitive to the cost of living at the destination, whereas business tourism demand was more sensitive to the cost of travel.

Capital investment in the tourism sector had a positive and significant impact on disaggregated and aggregated numbers of international tourist arrivals in Saudi Arabia. Consistently, the hypothesis that there is a positive impact of capital investment in tourism at the destination country on tourism demand flow in Saudi Arabia could not be rejected. VFR tourism demand was more sensitive to capital investments in the tourism sector factors. Trade openness positively and significantly affected business tourism demand, which supported the hypothesis that there is a positive and significant impact of trade openness on business tourism demand. Additionally, enhancing human rights and prosperity in the destination were major factors in explaining Saudi Arabia's inbound tourism demand for all models, except for the VFR model, in which human rights had no significant affect. This supports the hypothesis that there is a significant and positive impact of human rights and prosperity on Saudi inbound tourism demand. In addition, business tourism demand was more sensitive to enhancing human rights, whereas VFR tourism demand was more sensitive to destination prosperity.

Political risk had a negative impact on all tourism demand in Saudi Arabia, but was more important to religious tourism demand than to the other types of tourism demand under investigation. The hypothesis that there is a negative and significant impact of political risk on tourism demand flow in Saudi Arabia was supported. The global health risks factor was only significant for businesses and the total number of tourists. The regression findings supported the hypothesis that there is a negative and significant impact of global health risks on business tourism demand flow in Saudi Arabia, but rejected it for religious, VFR and the total tourism demand model. Relative temperature had a negative and significant effect on religious tourism demand and a significant but positive impact on the total number of tourists. The findings support the hypothesis that there is a significant impact of relative temperature only on religious and total tourism demand in Saudi Arabia.

There was a significant and positive impact of Saudi students studying overseas on VFR and total tourism demand flow in Saudi Arabia. The regression results supported the hypothesis of a significant and positive relationship between Saudi students studying overseas and VFR and total tourism demand flow in Saudi Arabia.

Visa restrictions had a significant and negative impact on religious, VFR and the total number of tourists, but with a greater influence on VFR travel demand than on religious and total tourism demand. This supports the hypothesis that there is a negative and significant impact of visa restrictions on religious, VFR, and the total number of tourists to Saudi Arabia.

Sharing a common religion between destination and origin countries only had a significant and positive impact on religious tourism demand. Sharing a common language between destination and origin countries also only had a significant impact on religious tourism demand but its impact was negative.

This study found that expatriate workers significantly and positively affected religious, business and total tourism demand in Saudi Arabia. This supports the hypothesis that there is a positive and significant impact of expatriate workers on religious, business and the total tourists flow in Saudi Arabia. However, expatriate workers significantly and negatively affected VFR tourism demand. Religious tourism demand was more sensitive to expatriate workers than other types of tourism demand under consideration.

Comparing aggregate and disaggregate tourism demand based on the purpose of visit (religious, business, and VFR) revealed important implications for international tourism since it may significantly impact the magnitude of the effect of economic and non-economic factors. In addition, some factors may only affect some tourists but not all. Therefore, it is essential to disaggregate international tourism demand according to the purpose of visit. Yet such studies are rare in the literature.

Table 8.1 below summarises the hypotheses developed to meet the first two objectives of this study.

Table 8.1. Hypotheses summary: Factors affecting international tourism demand by religious, business and VFR tourists in the long run

Research objective & hypothesis					
Objective (1): Develop holistic models for economic and selected non-economic factors that impact religious, business, and VFR tourist flows. **Objective (2): Identify the importance of these economic and selected non-economic factors on aggregate and disaggregate levels of international tourism demand.**					
	Variable/s	**Religious model analysis result**	**Business model analysis result**	**VFR model analysis result**	**Aggregate model analysis result**
Hypothesis E_1: The income of destination and origin countries has a positive and significant impact on all tourism demand flow in Saudi Arabia.	Income	$(+)^{***}$ Cannot reject E_1	$(+)^{***}$ Cannot reject E_1	$(+)^{***}$ Cannot reject E_1	$(+)^{***}$ Cannot reject E_1
Hypothesis E_2: Cost of living at the destination (tourism price) has a negative impact on tourism demand flow in Saudi Arabia.	Cost of living at the destination	(-)*** Cannot reject E_2	(-)*** Cannot reject E_2	(-) Reject E_2	(-)*** Cannot reject E_2
Hypothesis E_3: Travel cost has a negative and significant impact on tourism demand flow in Saudi Arabia.	Travel cost	$(-)^{***}$ Cannot reject E_3	$(-)^{***}$ Cannot reject E_3	$(-)^{***}$ Cannot reject E_3	$(-)^{***}$ Cannot reject E_3
Hypothesis E_4: Capital investment in tourism in the destination country has a positive impact on tourism demand flow in Saudi Arabia	Capital investment in tourism of the destination country	$(+)^{***}$ Cannot reject E_4	$(+)^{***}$ Cannot reject E_4	$(+)^{***}$ Cannot reject E_4	$(+)^{***}$ Cannot reject E_4
Hypothesis E_5: Trade openness has a positive impact on tourism demand flow in Saudi Arabia.	Trade openness	-	$(+)^{***}$ Cannot reject E_5	-	(+) Reject E_5
Hypothesis E_6: FDI in the destination country has a positive impact on business tourism demand flow in Saudi Arabia.	FDI	-	(+)	-	$(+)^{***}$ Cannot reject E_6
Hypothesis D_1: Enhancing human rights has a positive and significant impact of on tourism demand flow in Saudi Arabia.	Human rights	$(+)^{**}$ Cannot reject D_1	$(+)^{***}$ Cannot reject D_1	(+) Reject D_1	$(+)^{***}$ Cannot reject D_1
Hypothesis D_2 : Political risk has a negative impact on tourism demand flow in Saudi Arabia.	Political risks	$(-)^{***}$ Cannot reject D_2	$(-)^{***}$ Cannot reject D_2	$(-)^{***}$ Cannot reject D_2	$(-)^{***}$ Cannot reject D_2
Hypothesis D_3: Global health risk has a significant negative impact on tourism demand flow in Saudi Arabia.	Global health risks	(-) Reject D_3	$(-)^{***}$ Cannot reject D_3	(-) Reject D_3	(-)** Cannot reject D_3

Hypothesis D_4: The Hajj risk has had a negative and significant impact on religious tourism demand flow in Saudi Arabia.	Hajj incident	(-) Reject A_2	-		
Hypothesis D_5: The prosperity of the destination has a positive and significant impact on tourism demand flow in Saudi Arabia.	Prosperity of the destination	(+)** Cannot reject D_4	(+)*** Cannot reject D_4d	(+)** Cannot reject D_4	(+)*** Cannot reject D_4
Hypothesis D_6: The temperature ratio of the source market to the destination market has a significant negative impact on tourism demand flow in Saudi Arabia.	Relative temperature	$(-)^{***}$ Cannot reject D_5	(-) Reject D_5	(+) Reject D_5	(+)*** Cannot reject D_5
Hypothesis D_7: Students studying overseas have a significant positive impact on VFR demand flow in Saudi Arabia.	Students studying overseas	-	-	(+)*** Cannot reject D_6	(+)*** Cannot reject D_6
Hypothesis D_8: Visa restrictions have a significantly negative impact on tourism demand flow in Saudi Arabia.	Visa restrictions	$(-)^{***}$ Cannot reject D_7	-	$(-)^{***}$ Cannot reject D_7	$(-)^{***}$ Cannot reject D_7
Hypothesis D_9 : Sharing a common language has a positive and significant impact on tourism demand flow in Saudi Arabia.	Sharing a common language	(-)*** Reject D_8	(-) Reject D_8	(+) Reject D_8	(-) Reject D_8
Hypothesis D_{10} : Sharing a common religion has a positive and significant impact on tourism demand flow in Saudi Arabia.	Sharing a common religion	(+)*** Cannot reject D_9	(-) Reject D_9	(+) Reject D_9	(+) Reject D_9
Hypothesis D_{11}: Expatriate workers have a positive impact on tourism demand flow in Saudi Arabia.	Expatriate workers	(+)*** Cannot reject D_{10}	(+)*** Cannot reject D_{10}	(-)*** Reject D_{10}	(+)*** Cannot reject D_{10}
Hypothesis A_1: Word-of-mouth has a positive and significant impact on religious tourism demand flow in Saudi Arabia	Word-of-mouth	$(+)^{***}$ Cannot reject A_1	-		

Note: ***p < 0.01, **p < 0.05, *p < 0.1.

8.3.3. Addressing objectives three and four: Forecasting tourism demand growth rates

Chapter six addressed the findings relating to the third and fourth objectives. These were to forecast the growth rates of religious, business, and VFR tourist arrivals to Saudi Arabia. This was done by using the time series method, econometric method, and combination forecast method to generate in-sample forecasts and compare the performance of the forecasting models. This would provide the best possible forecast methods for how international tourism flows in Saudi Arabia**.**

The time series models used were ARMA, SES, and naive-1. The best model to forecast the growth rate of religious tourism demand was the SES model; for business tourism demand, the SES model was the best forecast model based on RMSE, whereas the ARMA model was the best forecast model based on MAPE. For VFR tourism demand, naive-1 was the best forecast model. Econometric forecasting methods were developed using ARDL, ECM, and VAR models. The ECM forecast model performed better for forecasting all purposes of visits (except business based on MAPE). The best model to forecast business tourism demand based on MAPE was the VAR model.

Forecasting combinations were also generated by combining time series models and econometric models using two forecast combination methods: SA and VACO. The SA method was best for forecasting religious and business tourism demand based on RMSE. However, the VACO model was best for forecasting religious and business tourism demand based on MAPE. The SA method generated the most accurate forecasts for VFR tourism demand based on both RMSE and MAPE. The results are summarised in Table 8.2.

Table 8.2. Best forecasting and combination forecast methods for the period 2017 to 2019

Research objective & hypothesis		
Objective (3): Use time series models, econometric models, and a combination forecast method to generate ex-post forecasting of religion, business, and VFR tourist arrivals to Saudi Arabia.		
	Best forecast model of time series methods	
Purpose of visit	**RMSE**	**MAPE**
Religious	Simple exponential smoothing model	
Business	Simple exponential smoothing model	ARMA
VFR	Naive-1	
	Best forecast model of econometric methods	
Purpose of visit	**RMSE**	**MAPE**
Religious	ECM	
Business	ECM	VAR
VFR	ECM	
	Best forecast method of combined methods	
Purpose of visit	**RMSE**	**MAPE**
Religious	SA	VACO
Business	SA	VACO
VFR	SA	

In order to test the hypothesis that econometric models provide better forecasting than time series methods within in-sample forecasting, the models were compared in Chapter six. The finding showed that, on average, the time series models performed better than the econometric models. The hypothesis that econometric methods provide better forecasting than time series methods within sample forecasting was rejected in all purposes of visit except the religious tourism demand based on MAPE (which meant the hypothesis could not be rejected, as shown in Table 8.3).

Table 8.3. Comparative forecasting accuracy of time series and econometric models

	Religious		Business		VFR	
The best forecast method – On average	**RMSE**	**MAPE**	**RMSE**	**MAPE**	**RMSE**	**MAPE**
	Time series	Econometric	Time series	Time series	Time series	Time series

The combination forecast methods were assessed to determine whether they provide better forecasts than the time series and econometric methods. As shown in Table 8.4, combined forecasts generated better forecasting compared to single time series and econometric forecasting for business and VFR tourism demand. However, for religious tourism demand forecasting, the time series method generated the best forecast for based on RMSE, whereas the econometric method generated the best forecast for religious tourism demand based on MAPE.

On average, combined forecasts performed better than the time series and econometric methods in most of the cases. This supports the hypothesis that combination forecasts provide a better forecast than the individual forecast methods for business and VFR tourism demand growth rates. Comparing the various estimated forecasting errors on average, the RMSE and MAPE gave the same ranking on most of the cases. It was concluded that combined methods forecasting may not necessarily provide more accurate estimates than selected individual forecasting methods.

Table 8.4. Comparative forecasting accuracy of time series, econometric, and combination forecasting models

Religious		Business		VFR	
RMSE	**MAPE**	**RMSE**	**MAPE**	**RMSE**	**MAPE**
Time series	Econometric	Combined forecasts	Combined forecasts	Combined forecasts	Combined forecasts

Table 8.5. Hypotheses for forecasting growth rates of religious, business and VFR tourism demand

Research objective & hypothesis	Religious		Business		VFR	
Objective (4): Compare the performance of forecasting models to provide the best possible forecast methods for how international tourism flows work in Saudi Arabia.	**RMSE**	**MAPE**	**RMSE**	**MAPE**	**RMSE**	**MAPE**
Hypothesis F_1: Econometric models provide better forecasting than time series models.	Reject F_1	Cannot reject F_1	Reject F_1		Reject F_1	
Hypothesis F_2: The combination forecasting method provides a better forecast than individual forecasting methods.	Reject F_2		Reject F_2		Reject F_2	

8.3.4. Addressing objective five: The impact of COVID-19 on tourism demand

Chapter seven addressed the findings relating to the fifth objective, which was to assess the impact of COVID-19 on Saudi Arabia's religious, business, and VFR tourism demand. QR, IRFs, and scenario analysis were employed to conduct this assessment. Scenario analysis and IRFs used annual data of the number of tourists from 2000 to 2019 as the dependent variable. The explanatory variables used were the income of both destination and origin country and data from the WUPI. QR used COVID-19-confirmed cases monthly data from 2020 and 2021 to examine the impact of the health risk on tourism demand (as the WUPI does not provide as monthly data).

QR estimates were applied to test the hypothesis that the health risk variable (measured by confirmed cases of COVID-19) had a significant negative effect on religious, business, and VAR tourism demand. QR allowed us to see how COVID-19 impacted different quantiles of tourism demand. In the low (20^{th}) quantiles of the number of tourist arrivals, the impact of COVID-19 was negative, indicating that an increase in one confirmed COVID-19 case led to a decrease in the number of tourist arrivals for religious, business and VFR purposes. Religious tourist arrivals were more impacted than VFR followed by business arrivals.

In the high quantiles, the negative impact of COVID-19 became less as restrictions eased and bans were lifted, allowing more tourists to travel again. All coefficients reduced as the percentiles increased. The impact of COVID-19 confirmed cases in reducing tourism demand was highest at the 20^{th} and 40th quantiles, but the impact became less in the 60^{th} and 80^{th} quantiles. For instance, the 80^{th} percentile tourism demand changed less with each unit change of confirmed COVID-19 cases than in the 20^{the} percentile tourism demand.

The hypothesis that the effect of confirmed cases of COVID-19 on tourism demand varied in different quantiles was also tested. The findings suggested that the assumption of equal slopes could not be accepted. There were statistically significant differences among quantiles that confirmed the heterogeneous impact of the confirmed cases of COVID-19 variable on tourism demand. This is relevant since it implies that when a research study is primarily focused on specific quantiles, linear models may lead to insufficient conclusions regarding whether there is a relationship between the explanatory and the dependent variables. This may lead to incorrect conclusions about the strength of the link. The test for symmetry between quantiles was statistically significant, which confirms the heterogeneous impact of the confirmed cases of COVID-19 variable on tourism demand for the three purposes of visit. Both hypotheses C_1 and C_2 could not be rejected, as shown in Table *8.6.*

Table 8.6. Hypothesis of quantile regression

Research objective & hypothesis	Analysis result		
Objective (5): Assess the impacts of the COVID-19 pandemic on religious, business and VFR inbound tourism demand for Saudi Arabia.	**Religious**	**Business**	**VFR**
Hypothesis C_1: The confirmed cases of COVID-19 variable has a significant effect on religious, business, and VFR tourism demand.	Cannot reject the hypothesis C_1		
Hypothesis C_2: The effect confirmed cases of COVID-19 on tourism demand varies across different quantiles.	Cannot reject the hypothesis C_2		

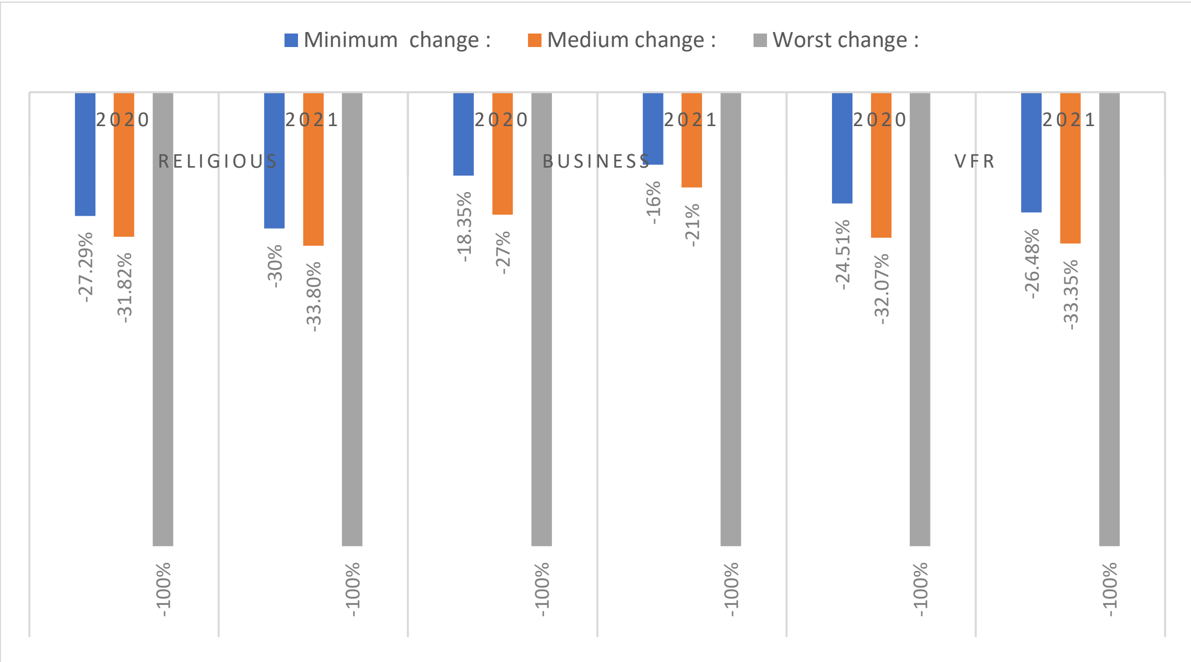
IRFs were used to evaluate the short and medium-run effects of a health risk shock and income on tourist arrivals. The empirical evidence from the IRFs suggested that health and income shocks led to a temporary decline in tourist arrivals. Interestingly, the effects were heterogeneous across the purpose of visits, but larger in religious tourism. Business tourism demand seemed to be less affected by the health and income shock. A shock in the health risk and income variables was associated with a significant decrease in the number of tourist arrivals. Tourism demand increased from period two after the shock. This increase was sharp in business tourism demands, which may indicate that business tourism demand recovered faster.

Using scenario analysis projections on inbound tourist flows, this study found that in the minimum change scenario in 2020, as GDP fell by 2.5 per cent, and health risks increased by 8.5 per cent, inbound tourist flows decreased by -27.2 per cent, -18.35 per cent, and -24.51 per cent for religious, business, and VFR respectively compared to the no-change model in 2020. In 2021, GDP grew by 1 per cent and health risks fell by 3 per cent (compared to 2020) and then compare this change to the no-change) scenario. Therefore, In the minimum scenario, inbound tourist flows decreased by -30 per cent, -16 per cent and - 26 per cent for religious, business, and VFR respectively compared to the no-change model in 2021.

-In Medium change scenarios in 2020, as GDP decreased by 4.5 per cent and health risk increased by 17 per cent compared to no change scenario, inbound tourist flows decreased by -31.82 per cent, -27 per cent, and - 32 per cent for religious, business, and VFR, respectively, compared to the no-change model in 2020. Whereas in 2021 GDP grew by 2.8 per cent and health risk decreased by 6 per cent compared to 2020, causing declines in religious, business, and VFR inbound tourist flows by -33 per cent, -21 per cent,-33 per cent respectively compared to the no-change model in 2021. This research indicates that the COVID-19 outbreak has had a significant and negative influence on Saudi Arabia's tourism economy. When governments have imposed travel restrictions and bans, it seems to lead to a loss of 100 per cent of inbound tourists. Figure 8.1 provides an overview of the scenario analysis findings.

This research indicates that the COVID-19 outbreak has had a significant and negative influence on Saudi Arabia's tourism economy. When governments-imposed travel restrictions and bans, this led to a loss of 100 percent of inbound tourists.

Figure 8.1. The impact of a possible change of tourism demand determinants on tourism compared to the no impact scenario for religious, business and VFR.



Three methodologies were used to demonstrate that religious tourism was the most affected by the epidemic and required a longer time to recover than VFR and business tourism. VFR tourism was impacted the least and recovered more quickly. A number of significant findings were revealed in the analysis, including that different visiting purposes were impacted differently by the pandemic. The health risk variable also impacted different quantile percentiles of tourism demand differently.

8.4. Practical implications of the research

This thesis provides policy support for Saudi Arabia's tourism-related industry and the Ministry of Tourism. It also provides some recommendations that can be taken by the Saudi authorities to maximise the benefits of the tourism sector.

The role of non-economic factors on tourism demand, such as destination prosperity, destination human rights, expatriate workers, and students studying overseas, have received little attention in previous research. The results of this current study show the importance of these factors in explaining tourism demand. Based on these results, this current study has important policy implications for countries that rely on tourism or seek to establish more robust and diverse tourism economies. The main implication for religious tourism is that offering higher quality services is critical for attracting new and repeat visitors. Since the cost of living in the destination is an important factor for religious tourism demand in Saudi Arabia, which represents the largest proportion of tourism demand, decreasing prices is a viable strategy to attract international tourists. Maintaining a steady cost of living and providing low budget travel and accommodation may assist in promoting inbound tourism demand in Saudi Arabia. Saudi Arabia should consistently expand its budget to support tourism investment and focus on international tourism promotion to attract more tourists and boost tourism earnings. It is crucial for the government of Saudi Arabia to monitor the economic performance of tourist-origin countries, as tourist income influences tourism demand in Saudi Arabia. Saudi Arabia's economic size has been demonstrated to be a significant factor in the country's tourist inflow. The government and industry operators must offer more tourism products and events in order to attract more tourists to Saudi Arabia and enhance the country's GDP. With sufficient capital, the government may further enhance the tourism infrastructure and facilities to ensure its competitiveness and attractiveness, leading tourists to realise that their money was well spent.

The fact that travel costs have a negative effect on Saudi Arabia's demand for tourism, especially business tourism, supports the gravity model, which suggests the increased cost of travel leads to a decrease in the number of tourists to the destination. To grow business tourism in Saudi Arabia, the government needs to know how important travel costs are in shaping and growing its tourism sector. Moreover, Saudi Arabia may also need to increase the number of international airports, upgrade the standard of existing airports, and introduce low-cost airlines.

Destination prosperity can be an attractive feature for tourists. To promote the image of a safe and secure country, along with a good quality of life, Saudi Arabia should invest in a high standard of health care, a clean environment, skilled human resources, high-quality services, transportation infrastructure, and technology, thereby making travel safe and memorable.

To enhance tourism development in the future, more foreign investors should be attracted. The positive role of trade openness suggests that the country can enhance FDI inflow by reducing trade barriers in the form of various customs taxes and duties. FDI is believed to be a significant factor in increasing competitiveness, innovation, labour productivity, and economic diversification, thereby boosting tourism demand. Authorities should take various steps to attract FDI inflow, including facilitating a comprehensive legislative structure and enhancing bureaucratic quality. Additionally, the country should expand multilateral and bilateral trade and financial integration agreements with a variety of potential governments.

Given that political risk is found to be negatively associated with inbound tourism, Saudi Arabia should seek to minimise both internal and external political conflicts, wars, and instabilities for the benefit of tourism. In this context, Saudi Arabia could initiate international peace conferences, enhance economic and trade cooperation, and promote regional trade ties and FDI. In addition, international institutions should introduce new peace agreements and reinforce existing ones. It would be useful for governments and policymakers to monitor and manage the socio-economic factors that could cause political risks, including poverty, religious extremism, corruption, unemployment, and income disparity.

Moreover, as demonstrated in this study, respect for human rights at the destination can also increase tourism demand. While the impact of enhancing human rights in the destination country is not directly related to tourists, it can influence their perception of safety and security. Therefore, the government should prioritise efforts to protect and promote human rights by enacting stable regulations and laws that safeguard the rights of women, children, and expatriate workers. This can improve the country's image and boost its economic growth by attracting more tourists. Tourism authorities should play an active role in this effort.

Tourism is significantly affected by visa restrictions. Therefore, policymakers should consider whether the benefits of relaxing visa controls outweigh any security and other concerns they may have. While there is a limited time each year for Hajj participation, those who travel to Saudi Arabia could also be given an additional tourist visa to explore other sites of historical or recreational interest, particularly those that are close to the holy cities of Mecca and Madinah, where the Hajj is performed. This would assist the hospitality, travel, and tourism sector to grow in Saudi Arabia.

This study empirically proves the positive impact of expatriate workers on inbound international tourism to Saudi Arabia. Consequently, trends in immigration flows have an impact on trends of international tourist arrivals. These elasticities are expected to assist the government and destination managers in policy creation and implementation.

Destination marketing organisations can play a significant role in promoting VFR tourism by educating community members, especially residents, regarding local tourism attractions and encouraging them to share this information with their friends and family. Media, in general, can also be employed to spread such information. Saudi students studying overseas have a positive impact on VFR tourism demand by visiting their country in their holidays, they also can play a marketing role by raising awareness of their home country in their study destination.

In the context of the COVID-19 pandemic's significant impact on tourism demand, this study has provided critical insights to assist tourism policymakers and practitioners in developing effective initiatives and recovery strategies. This will build tourists' confidence after the health risk crisis and reduce the negative impact of the COVID-19 pandemic on tourism. Although the number of cases and deaths has been reduced by vaccination programs, governments should identify effective methods to control the pandemic and facilitate future travel. It is essential to ensure that appropriate safety measures are in place at airports and that everyone follows standard operating procedures. As a result, tourists' confidence in Saudi Arabia's safety would be enhanced whether they visit for religious or non-religious purposes.

Moreover, with an understanding of the forecasting models developed in this study, Saudi Arabia's relevant authorities should take a realistic approach to forecasting future tourism demand using scientific methods. This will assist future planning and investment in the tourism industry.

In conclusion, modelling tourism based on the purpose of visit provides policymakers with valuable insights into tourist behaviours, enabling targeted marketing and promotion, infrastructure planning, revenue generation, and the development of policy frameworks that support sustainable tourism. These findings can guide policymakers in making informed decisions, enhancing the overall tourism experience, and maximising the economic, social, and environmental benefits of tourism.

8.5. Contribution of the thesis

Although previous studies have contributed considerable knowledge to the area of tourism demand, there has been a lack of research in some aspects of selected destinations, determinants of tourism demand, and the econometric approach. These gaps provided important motivation for the research presented in this thesis and the resulting findings make a significant contribution to the literature on tourism demand.

To begin with, tourism research studies have primarily been conducted in developed countries for both origin and destination countries, with only a few focused on developing countries in the Asia-Pacific region. There are significant differences between the tourism potential and characteristics of these regions and those of Saudi Arabia, which has received a limited amount of academic attention, both in terms of the number of studies and the technical approaches. The findings of this study have provided a better understanding of tourism in Saudi Arabia, one of the most popular tourist destinations in the

Middle East. Therefore, this study provides an opportunity for further research into Middle Eastern tourism, specifically Saudi Arabia.

Moreover, studies in tourism demand literature usually analyse total tourism arrivals, although there is general recognition that different types of tourists respond differently to changes in economic and non-economic factors. Disaggregate tourism demand, and forecasting models based on visiting purposes have only been minimally investigated, and the three markets of religious, business and VFR tourists have not been compared in the literature. This may be due to data constraints, meaning that aggregate flows may dominate. Modelling at a more disaggregate level to reflect the heterogeneity of tourism demand has proved more effective. This is supported by this study, in which considerable differences were found in the nature and magnitude of the effect of independent variables on various types of demand.

Several studies on tourism demand have investigated tourism in a more disaggregated context by examining the impact of economic and non-economic factors on different types of tourism, including Bulut et al. (2020), Doğan et al. (2022), and Ghosh (2021). Previous studies, such as Kusni et al. (2013), and Naudé and Saayman (2005), have emphasised that economic and non-economic factors should be considered in modelling international tourism demand in developing countries. Others have noted that non-economic factors may be of equal value to economic factors when considering tourism demand (O'Hagan & Harrison, 1984). This study considered economic and non-economic factors as determinants of tourism demand, and both showed significant impact.

Furthermore, this thesis used a more comprehensive analysis in selecting the factors that influence tourism demand, introducing new variables not previously included in the tourism demand literature (i.e., enhancements in human rights in the destination, the prosperity of the destination, the existence of foreign workers, and the number of Saudi students studying overseas). These factors showed significant impact on tourism demand, so this study provides a potential source for further research that explores the impact of destination prosperity, human rights, expatriate workers, and international students studying overseas on tourism demand.

While several studies have been conducted to forecast tourist arrivals to other countries (Chatziantoniou et al., 2016; Jiao et al., 2020; Law et al., 2019; Song et al., 2019; Zhu et al., 2018) none of these studies take non-economic factors into account, or different visiting purposes. Furthermore, using time series techniques only does not provide policy recommendations as this technique only depends on the historical data of the series to generate predictions about future time series values (Lin & Song, 2015; Saayman & Saayman, 2008; Zhu et al., 2018). Therefore, there is a need to expand on forecasts of tourism demand using the econometric method to explore the relationships between tourist arrivals and their determinants. The findings of various studies are not conclusive and the performance vagueness in time series and econometric models suggests an emerging trend in the use of combined methods for tourism demand. Using a combination of forecasts from different forecasting methods can improve the accuracy of forecasts, since it can minimise errors (Song et al., 2019). According to Lee (2005), Veloce (2004), and Wu and Blake (2022), the aim of the combined forecasting method is to achieve a more reliable and accurate forecast by incorporating the advantages of various forecasting models.

Only a limited number of studies have examined the impact of COVID-19 on the disaggregated level (purpose of visit) of tourism demand, to investigate the sensitivity of each market to the pandemic and refine the current understanding of COVID-19. This study employed three analysis tools to assess the impact of a pandemic on tourism demand, using a new index (WUPI) to measure health risks as well as data for the number of confirmed infection cases. There is no doubt that considering the diverse types of tourism, the findings of this study provide policymakers with important indicators in terms of directing efforts to recover the tourism industry post-pandemic.

8.6. The study's limitations

Despite significant attempts to ensure the objectives were achieved, it should be recognised that the study had several data limitations. First, no countries from the Americas or Europe (except the UK and the US in business tourism demand) were included in the analysis due to the low number of tourists from these regions during the study period. This may have an impact on the generalisability of the results in these two regions. Another limitation relates to the availability of data. No data was available for the number of tourists flows before 2000 and after 2019, and, of course, the COVID-19 pandemic affected 2020 and 2021 data, providing both a challenge and an opportunity.

8.7. Suggestions for future research

The following are some suggestions for avenues of future research that have arisen out of this study:

- Clearly, it would be useful to analyze the seasonal influence on tourism demand through more studies based on monthly or quarterly series, when the data is available.
- While this study disaggregated tourism demand for Saudi Arabia by tourists' purpose of visit, additional research could classify tourists by other factors such as development status of country of origin, economic level, social group, gender or age.
- Although the prosperity and human rights variables proved to be relevant and had a significant effect on tourism demand for Saudi Arabia, more empirical studies are needed to examine and validate the usefulness of these factors in modelling international tourism demand for other destinations.
- To validate the results, the models in this study could be tested in future studies using another estimate method, such as system GMM (SYS-GMM).

- Survey data in future research may assist in learning more about other factors influencing whether tourists visit Saudi Arabia.
- In this study, the sample of international tourist arrivals differs based on the purpose of visit, because Saudi tourism market diversification is limited and the biggest reason for visiting is for religious purposes. Future studies could use the same sample of countries for all visiting purposes when the data is available to compare.
- This study considered the total score of the prosperity index rather than its deconstructed components. Future research could investigate the role of decomposed components of prosperity in explaining tourism inflows to Saudi Arabia, to improve our understanding of the tourism-prosperity nexus.
- Future studies could also explore advanced forecasting methods to forecast Saudi Arabian tourism demand.

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APPENDICES

Appendix A: Summary of key studies that have used gravity models.

Author (year)	Region Focused	Estimation method	Independent variables
Quandt and Young (1969)	US	Linear and non-linear regression	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; sociological and cultural variables; economic variable; travel costs.
Crampon and Tan (1973)	Pacific and Far East	Linear regression	Distance (geographical, travel distance); GDP of origin country; Population at origin country; travel costs.
Smith and Brown (1981)	Canada	Linear regression	Distance (geographical, travel distance); Population at origin country; Population at destination country.
Saunders et al. (1981)	US	Linear regression	Distance (geographical, travel distance,); Population at origin country; sociological and cultural variables; environmental variables.
Quandt and Baumol (1992)	US	Linear regression	GDP of origin country; Population at origin county; Variables related to sociological and cultural variables; Variables related to economic variables; Variables related to travel costs.
Muhammad and Andrews (2008)	Uganda	POLS; Panel-FE	Distance (geographical, travel distance); GDP of origin country; Variables related to exchange rate; Common border, contiguity, neighbouring countries; Variables related to trade (export, imports, total trade, trade openness).
Archibald et al. (2008)	Caribbean	Dynamic panel data model (GMM) and Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to exchange rate; Variables related to price indicators (CPI, PPP); Variables related to travel costs.
Durbarry (2008)	UK	Panel-FE and Panel-RE	GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to exchange rate; Variables related to price indicators (CPI, PPP); Common language, official language, spoken languages; Geographical variables (island coastline, beaches, area, landlocked).
Khadaroo and Seetanah (2008)	28 countries	Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to price indicators; Common border, contiguity, neighbouring countries; Common language, official language, spoken languages; Tourism and transport infrastructures; Variables related to air connectivity (direct flights accessibility, influence of LCC).
Seetanah et al. (2010)	South Africa	FMOLS	Distance (geographical, travel distance) ; GDP of origin country; GDP of destination country; Variables related to exchange rate; Variables related to price indicators ; Common border, contiguity, neighbouring countries; Common language; Tourism and transport infrastructures; Sharing a common currency, official currency,.; Political issues related to government effectiveness and institutional quality.
Leitão (2010)	Portugal	Panel-FE and dynamic panel (GMM)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Variables related to trad.

Yang et al. (2010)	China	POLS ; Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Variables related to exchange rate; Geographical variables; Tourism and transport infrastructures; Security issues (terrorism, crime, armed conflicts); World Heritage Sites; Cultural affinity; sociological and cultural variables; Special events (SARS; mega-events, crises, natural disasters, Arab Spring).
Hanafiah and Harun (2010)	Malaysia	Linear regression	Distance (geographical, travel distance); GDP of origin country; Population at origin country; ; Population at destination country; Variables related to trade.
Song (2010)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country;; Special events ; Common border; Common language; Geographical variables ; Free Trade Agreements, trade blocks; Colonial relationship; Sharing a common currency.
Rey et al. (2011)	Spain	GMM-DIFF procedure	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Special events; Variables related to travel costs; Variables related to price indicators; Tourism and transport infrastructures; Variables related to air connectivity.
Fourie and Santana-Gallego (2011)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Common border; official language; Variables related to trade; Colonial relationship; Sharing a common currency; Special events.
Vietze (2012)	US	POLS ; Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; official language; Geographical variables; Political issues related to government effectiveness and institutional quality; Security issues (terrorism, crime, armed conflict,); Visa policy; Variables related to religion (religion affinity, major religion).
Huang et al. (2012)	Macau	Panel-FE; Panel-RE	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Tourism and transport infrastructures; Security issues; World Heritage Sites; Special events.
Genç (2013)	New Zealand	FE and RE panel model	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to exchange rate; Common language; Variables related to migration.
Balli et al. (2013)	Turkey	Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; official language; Visa policy; Variables related to religion; Variables related to trade; sociological and cultural variables; Tourism and transport infrastructures; Variables related to exchange rate.
Velasquez and Oh (2013)	Peru	Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to exchange rate; Variables related to price indicators; Common border; official language; Visa policy.
Patuelli et al. (2013)	Italy	FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators ; Geographical variables; Tourism and

			transport infrastructures; sociological and cultural variables; Security issues; World Heritage Sites; Cultural affinity (cultural products, cultural distance).
Fourie and Santana-Gallego (2013)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to exchange rate; Common border; Common language; Colonial relationship; Sharing a common currency; Variables related to migration; Free Trade Agreements.
Fourie and Santana-Gallego (2013)	World/Africa	POLS and Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to exchange rate; Common border; Common language; Colonial relationship; Sharing a common currency; sociological and cultural variables; Tourism and transport infrastructures; Variables related to migration; Free Trade Agreements; Variables related to trade; Variables related to religion; Geographical variables.
Zhang and Findlay (2014)	APEC members	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Common language; Variables related to air; connectivity Common border; Geographical variables.
Rosselló and Santana-Gallego (2014)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Common language; Common border; Geographical variables; Variables related to climate.
De Vita (2014)	OECD	Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Variables related to exchange rate; Common border; Common language; Free Trade Agreements; Variables related to trade; Sharing a common currency; Colonial relationship; Economic variables (military spending, taxes, unemployment, public spending).
Deluna Jr and Jeon (2014)	Philippines	Panel-RE	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to price indicators; Variables related to exchange rate; Common language; Free Trade Agreements; Colonial relationship; Political issues related to government effectiveness and institutional quality; Variables related to air connectivity; Special events.
Culiuc (2014)	World	POLS ; Panel-FE; Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to exchange rate; Common border; Common language; Free Trade Agreements; Variables related to trade; Sharing a common currency; Colonial relationship; Tourism and transport infrastructures; Time Zone. Security issues.
Chasapopoulos et al. (2014)	Greece	Dynamic Panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Variables related to exchange rate; Variables related to trade; Tourism and transport infrastructures; Political issues related to government effectiveness and institutional quality. Special events.

Cheung and Saha (2015)	Australia	POLS ; QR	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Common language; Variables related to religion; Economic variables.
Priego et al. (2015)	Spain	POLS	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Special events; Geographical variable; Common border, contiguity, neighbouring countries; Variables related to climate.; World Heritage Sites.
Fourie et al. (2015)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; Common language; Sharing a common currency; Colonial relationship; Political issues related to government effectiveness and institutional quality; Geographical variables; Variables related to climate.
Fourie et al. (2016)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; Common language; Sharing a common currency; Colonial relationship; Political issues related to government effectiveness and institutional quality; Variables related to religion; Geographical variables; Variables related to climate.
Artal-Tur et al. (2016)	World	POLS ; PPML	Distance (geographical, travel distancer; Common language; Colonial relationship; Political issues related to government effectiveness and institutional quality; Variables related to migration; Variables related to trade; Free Trade Agreements; Visa policy.
Neumayer and Plümper (2016)	Islamic countries	PPML	GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Security issues (terrorism, crime, armed conflicts).
Saayman et al. (2016)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to trade; Free Trade Agreements; Variables related to price indicators; Common border; Common language; Sharing a common currency; Colonial relationship.
Santana-Gallego et al. (2016)	European Union/ OECD	Panel-FE	Sharing a common currency, Free Trade Agreements.
Santeramo and Morelli (2016)	Italy	Panel data QR	Distance; GDP of origin country; Population at origin country; Sharing a common currency; Sharing a common currency, sociological and cultural variables; Tourism and transport infrastructures; Visa policy**.**
Voltes-Dorta et al. (2016)	Spain	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Geographical variables; Special events; Security issues.
Lorde et al. (2016)	Caribbean	Dynamic panel data (GMM)	GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Variables related to climate; Variables related to travel costs; Economic variables.
Malaj and Kapiki (2016)	Greece	Panel-RE	Distance (geographical, travel distance); GDP of origin country; Political issues related to government effectiveness and institutional quality; Tourism and transport infrastructures; Variables related to climate.

Ghani (2016)	Malaysia	POLS and QR	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to religion.
Balli et al. (2016)	OECD	POLS and Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Common language; Colonial relationship; Common border; Variables related to exchange rate; Variables related to price indicators; Variables related to trade; Political issues related to government effectiveness and institutional quality; Special events; Variables related to migration.
Kaplan and Aktas (2016)	Turkey	PPML	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Common border; Free Trade Agreements. Special events.
Karaman (2016)	Turkey	POLS ; Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Common border; Geographical variables; Variables related to trade; Visa policy**.**
Akter et al. (2017)	Bangladesh	Panel-RE (GLS)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Variables related to price indicators.
Álvarez-Díaz et al. (2017)	Spain	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Geographical variables; Variables related to air connectivity; Tourism and transport infrastructures.
Gouveia et al. (2017)	Portugal	POLS ; Panel-RE; Panel-FE	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Variables related to price indicators; Sociological and cultural variables; Sharing a common currency.
Fourie and Santana-Gallego (2017)	South Africa	Panel-FE	GDP of origin country; Political issues related to government effectiveness and institutional quality; Special events.
Czaika & Neumayer (2017)	World	PPML	Distance (geographical, travel distance); Variables related to migration; Visa policy; Time Zone; Colonial relationship; Common border; Geographical variables.
Provenzano and Baggio (2017)	EU28	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Common border; Common language; Colonial relationship; Variables related to migration.
Yazdi et al. (2017)	USA	ARDL	GDP of origin country; Variables related to price indicator; Variables related to exchange rate; Variables related to air connectivity; Special events.
Tavares and Leitao (2017)	Brazil	POLS and Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Variables related to exchange rate ;Common border; Common language.
Rosselló et al. (2017)	World	POLS	Distance (geographical, travel distance); GDP of destination country; Population at destination country; Common border; Common language; Colonial relationship; Free Trade Agreements; Political issues related to government effectiveness and institutional quality; Security issues; Variables related to climate; World Heritage Sites; Variables related to religion; Sociological and cultural variables; Special events.
Groizard and Santana-Gallego (2018)	Arab countries	POLS and Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common language; Colonial relationship; Common border; Free Trade

			Agreements; Political issues related to government effectiveness and institutional quality; Variables related to religion; Security issues; World Heritage Sites.
Balli et al. (2018)	GCC	Panel-FE	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Common language; Colonial relationship; Common border; Political issues related to government effectiveness and institutional quality; Variables related to religion; Variables related to trade; Time Zone; Variables related to climate; Variables related to migration; Special events.
Adeola et al. (2018)	Africa	Dynamic panel data model (GMM)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Political issues related to government effectiveness and institutional quality; Sociological and cultural variables.
Tsui et al. (2018)	New Zealand	POLS ; Panel-FE; Panel-RE	Distance (geographical, travel distance); GDP of origin country; Tourism and transport infrastructures; Variables related to trade; Visa policy; Variables related to air connectivity; Special events.
Siskos and Darvidou (2018)	European countries	POLS	Distance (geographical, travel distance); GDP of origin country.
Ghalia et al. (2019)	World	POLS ; Panel-FE; PPML	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Common language; Colonial relationship; Political issues related to government effectiveness and institutional quality; Economic variables.
Ghani (2019a)	Muslim countries	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Common border; Common language; Colonial relationship; Variables related to religion.
Ghani (2019b)	Muslim countries	POLS; Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Common language; Colonial relationship; Variables related to religion.
Khalid et al. (2019)	World	POLS ; Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Common border; Common language; Colonial relationship; Geographical variables; Economic variables; Special events.
Butler and Suntikul (2019)	Turkey	Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; Variables related to trade; Special events.
Chow and Tsui (2019)	China	POLS ; Panel-FE; Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Variables related to exchange rate; Common border; Tourism and transport infrastructures; Variables related to trade; Variables related to air connectivity; Security issues.

Petit and Seetaram (2019)	OECD	POLS and PPML	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common language; Colonial relationship; Cultural affinity.
Sun and Lin (2019)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Economic variables; Geographical variables; Tourism and transport infrastructures; Variables related to trade; Variables related to air connectivity; Security issues. Variables related to air connectivity; Sociological and cultural variables; Visa policy; Variables related to migration.
Zhang et al. (2019)	World	Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Sociological and cultural variables; Cultural affinity; Political issues related to government effectiveness and institutional quality.
Balli, Ghassan, et al. (2019)	GCC	Dynamic panel data (GMM)	GDP of destination country; Variables related to price indicators; Variables related to exchange rate; Variables related to trade; Political issues related to government effectiveness and institutional quality; Special events ; Variables related to migration.
Breda and Oddo (2019)	Italy	Panel-FE	GDP of origin country; Population at origin country Variables related to price indicators; Variables related to exchange rate; Variables related to travel cost.
Xu et al. (2019)	China	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Variables related to price indicators; Free Trade Agreements; Cultural affinity; Political issues related to government effectiveness and institutional quality ;Economic variables; Special events.
Vítová et al. (2019)	Small Islands Development States	Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Variables related to trade; Common language; Colonial relationship; Political issues related to government effectiveness and institutional quality; Tourism and transport infrastructures variables; Variables related to climate.
Vierhaus (2019)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Common language; Colonial relationship; Common border; Free Trade Agreements; Special events; Sharing a common currency; Geographical variables.
Groizard et al. (2019)	Arab countries	PPML	GDP of destination country; Population at destination country; Security issues; Political issues related to government effectiveness and institutional quality; Variables related to religion.
Puah et al. (2019)	Vietnam	POLS ; Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators.
Montant (2020)	French Polynesia	POLS ; Panel-RE; PPML	Distance (geographical, travel distance); Variables related to price indicators; Political issues related to government effectiveness and institutional quality; Tourism and transport infrastructures; Variables related to exchange rate.

Provenzano (2020)	EU28	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Common border; Common language; Colonial relationship; Sharing a common currency; Variables related to migration.
Eric et al. (2020)	Kenya	POLS ; PPML; Panel-FE and Panel-RE	GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to travel costs; Security issues; Political issues related to government effectiveness and institutional quality; Variables related to trade; Variables related to air connectivity.
Ghosh (2020)	Australia	Common correlated effects (CCE)	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Variables related to price indicators; Variables related to exchange rate; Economic variables; Political issues related to government effectiveness and institutional quality.
Rosselló et al. (2020)	World	POLS	GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Security issues; Free Trade Agreements; Special events.
Jong et al. (2020a)	Sabah (Borneo)	POLS ; Panel-RE; Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; Common language; Political issues related to government effectiveness and institutional quality.
Xu and Dong (2020)	China	POLS ; GMM-IV	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Variables related to price indicators; Variables related to trade; Visa policy; Tourism and transport infrastructures; Variables related to climate; Environmental indicators (emissions, global warming); Sociological and cultural variables.
Adeola and Evans (2020)	Africa	Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Visa policy; Tourism and transport infrastructures; Variables related to climate; Environmental indicators (emissions, global warming); Sociological and cultural variables.
Ulucak et al. (2020)	Turkey	FMOLS and DOLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to exchange; Variables related to price indicators; Economic variables; Political issues related to government effectiveness and institutional quality.
Huang et al. (2020)	China	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to exchange; Variables related to trade; Visa policy; Cultural affinity; Political issues related to government effectiveness and institutional quality; Common border.
Khalid, Okafor and Aziz (2020)	World	POLS ; Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Common language; Colonial relationship; Geographical variables; Economic variables; Security issues.

Fourie et al. (2020)	World	Panel-FE	GDP of origin country; GDP of destination country; Variables related to price indicators; Free Trade Agreement; Security issues.
Waqas-Awan et al. (2021)	World	POLS	GDP of origin country; Population at origin country; Political issues related to government effectiveness and institutional quality; Security issues.
Tang (2021a)	Japan	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Political issues related to government effectiveness and institutional quality; Tourism and transport infrastructures; Sociological and cultural variables; Free Trade Agreements.
Altaf (2021)	India	POLS ; FGLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Variables related to price indicators; Variables related to trade.
Okafor and Khalid (2021)	World	POLS ; Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Geographical variables; Common language; Colonial relationship; Political issues related to government effectiveness and institutional quality.
Okafor, Tan, et al. (2021)	China	Panel-FE; Panel-RE; PPML	Distance (geographical, travel distance); GDP of destination country; Population at origin country; Variables related to price indicators; Common border variables; Common language; Colonial relationship; Geographical variables; Special events.
Panzera et al. (2021)	Europe	Bayesian multilevel model	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Geographical variables**;** World Heritage Sites.
Gani and Clemes (2021)	New Zealand	POLS ; Panel-FE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common language; Variables related to religion; Security issues; Political issues related to government effectiveness and institutional quality.
Gavriilidis (2021)	World	POLS	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border variables; Common language; Colonial relationship; Sociological and cultural variables.
Lopez et al. (2021)	Switzerland	POLS ; Panel-FE; Panel-RE	Distance (geographical, travel distance); GDP of origin country; Population at origin country; Variables related to exchange rate; Free Trade Agreements.
Khalid et al. (2021a)	Word	POLS ; PPML	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; Geographical variables; Common language; Colonial relationship; Free Trade Agreements.
Ibragimov et al. (2021)	Central Asia	POLS ; Panel-FE; Panel-RE	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Variables related to price indicators; Common border; Common language; Political issues related to government effectiveness and institutional quality.

Khan et al. (2021)	UK	Residual-based bootstrap	GDP of origin country; Variables related to exchange rate; Tourism and transport infrastructures; Political issues related to government effectiveness and institutional quality.
Cevik (2022)	World	POLS ; PPM	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Colonial relationship; Special events.
Shah et al. (2022)	India	Two-step panel FE model	GDP of origin country; Variables related to exchange rate; Variables related to price indicators; Common border; Common language.
Tong et al. (2022)	Thailand	System GMM model estimation	GDP of destination country; Variables related to exchange rate; Variables related to price indicators; Distance (geographical, travel distance); Political issues related to government effectiveness and institutional quality.
Cro et al. (2022)	Madeira (Portugal)	Dynamic panel data (GMM)	Distance (geographical, travel distance); GDP of origin country; Variables related to price indicators; Variables related to air connectivity; Variables related to climate; Geographical variables; Special events.
Okafor et al. (2022)	World	POLS ; 2SLS; PPML	GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common language; Variables related to price indicators; Variables related to migration.
Khalid et al. (2022)	Word	POLS ; PPML	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Common border; Geographical variables; Common language; Colonial relationship.
Heriqbaldi et al. (2023)	Southeast Asia	FGLS and PPML	Distance (geographical, travel distance); GDP of origin country; GDP of destination country; Population at origin country; Population at destination country; Cultural affinity; Variables related to price indicators; Economic variables; Variables related to exchange rate; Security issues.

Appendix B: Estimation results of FE and RE religious tourism demand

The dependent variable is number of religious tourist arrivals from 2000 to 2019

Independent variables	FE model	RE model
Economic factors		
Saudi income **ID_j**	2.890*** (0.000)	2.617*** (0.000)
Origin income **IO_i**	0.3640** (0.013)	0.2130*** (0.003)
Cost of travel **CT_{ij}**	-0.4280** (0.020)	-0.405** (0.010)
Cost of living at the destination **P_{ij}**	-0.1430** (0.065)	-0.023 (0.943)
Capital investment in the tourism sector **$INVEST_j$**	1.286 (0.205)	1.224 (0.238)
Non-economic factors		
Relative temperature **TEM_{IJ}**	-0.3560*** (0.002)	0.2960*** (0.008)
Human rights **HI_j**	0.724** (0.058)	0.763*** (0.035)
Political risk **$PRISK_j$**	-0.253** (0.012)	-0.2920*** (0.000)
Prosperity index **PI_j**	0.0100** (0.056)	0.010** (0.061)
Global health risk **HR**	-0.2530** (0.022)	-0.0800** (0.079)
Visa restrictions **DVR_J**	-	-0.3390** (0.015)
$Language_{ij}$	-	-0.532*** (0.003)
$Religion_{ij}$	-	1.0550*** (0.000)
R-squared	0.747	0.414
Adjusted R-squared	0.710	0.390
F-statistic **Prob (F-statistic)**	20.421 (0.000)	17.277 (0.000)

Source: Author's own calculations using EViews. *Note:* *p < 0.10, **p < 0.05, ***p < 0.01. The p-value is in parentheses.

Appendix C: Estimation results of FE and RE business tourism demand

The dependent variable is number of business tourist arrivals from 2000 to 2019

Estimation results		
	FE model	**RE model**
Variable	Coefficient Prob.	Coefficient Prob.*
Saudi income **IOj**	1.798*** (0.008)	0.027 (0.285)
Origin income $\mathbf{ID_i}$	0.694*** (0.019)	0.337*** (0.008)
Cost of travel $\mathbf{CT_{ijt}}$	-0.885*** (0.000)	-0.102 (0.500)
Cost of living at the destination $\boldsymbol{P_{ij}}$	-0.037 (0.761)	-0.064 (0.365)
Trade openness $\mathbf{TADE}_{ji}$	0.421*** (0.000)	0.252** (0.084)
Capital investment in the tourism sector at the destination $\boldsymbol{INVEST_j}$	0.021 (0.959)	-0.263 (0.549)
Foreign direct investment $\boldsymbol{FDI_j}$	0.055 (0.262)	0.009 (0.845)
Human rights index $\boldsymbol{HI_J}$	0.155** (0.084)	-0.003 (0.987)
Prosperity index $\boldsymbol{PI_J}$	0.130*** (0.000)	0.138*** (0.000)
Global health risk **HR**	-0.010** (0.074)	-0.003 (0.928)
Political risk $\mathbf{PRISK}_J$	-0.378*** (0.000)	-0.149 (0.167)
Relative temperature $\boldsymbol{TEM_{JI}}$	1.422 (0.714)	0.451 (0.689)
$\mathbf{Language}_{ij}$	-	-0.085 (0.861)
$\mathbf{Religion}_{ij}$	-	-0.490 (0.405)
C	-18.330 (0.015)	-13.702 (0.043)
R-squared	0.77	0.414
Adjusted R-squared	0.710	0.390
F-statistic **Prob(F-statistic)**	20.421 (0.000)	17.278 (0.000)

Note: *** 1% significant, **5% significant and * 10% significant.

Appendix D: Estimated results of VFR tourist arrival parameters using FE and RE models

The dependent variable is number of VFR tourist arrivals from 2000 to 2019.

	FE model	RE model
Variable	Coefficient Prob.*	Coefficient Prob.*
Cost of travel **CT_{ij}**	-0.222 (0.054)	-0.222** (0.054)
Cost of living at the destination P_{IJ}	-0.117 (0.238)	0.134*** (0.031)
Saudi income ID_J	1.331*** (0.000)	1.439*** (0.000)
Origin income IO_I	0.065** (0.060)	0.002** (0.071)
Capital investment $INVEST_J$	0.302 (0.414)	0.148 (0.686)
	Non-economic factors	
Prosperity index PI_J	3.097*** (0.003)	2.653*** (0.007)
Global health risk HR	-0.042 (0.187)	-0.044 (0.162)
Political risk **$PRISK_J$**	-1.562*** (0.006)	-1.684*** (0.003)
Relative temperature TEM_{JI}	0.212 (0.114)	0.213 (0.110)
Human rights index HI_J	0.301** (0.066)	0.398*** (0.009)
Saudi student study overseas **$OVESTU_{ij}$**	0.236*** (0.001)	0.269*** (0.000)
$Language_{ij}$	-	0.0726 (0.388)
$Religion_{ij}$	-	0.0466 (0.965)
Visa restrictions	-	-1.177*** (0.000)
R-squared	0.787	0.184
Adjusted R-squared	0.764	0.167
F-statistic **Prob(F-statistic)**	32.675 (0.000)	33.190 (0.000)

Source: Author's own calculations using EViews. *Note:* *** 1% significant, **5% significant and * 10% significant.