Assessment of Potential Insider Trading in the Saudi Stock Exchange Before and After the Introduction of Financial Reforms: An Event Study Market Cleanliness Methodology

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Abstract

The purpose of this research is to investigate the impact of the amended regulatory changes introduced with financial reforms in 2016 on the integrity of the Saudi Stock Exchange (Tadawul) with a particular focus on potential insider trading practice. The major objectives seek to assesses and compares the level of potential insider trading in the Tadawul over periods both before and after the introduction of financial reforms. The level of possible insider trading is estimated by employing an event study market cleanliness methodology that identifies the ratio of significant announcements (SAs) that were preceded by abnormal pre-announcement price movements (APPMs) and abnormal pre-announcement volumes (APAVs).

The research question is examined using a sample consisting of 1,958 unscheduled announcements published by firms listed in the Tadawul from 26 April 2011 to 25 April 2020 (the relevant period). The study uses event study approaches with daily stock returns and trading volumes to find evidence of APPMs and APAVs that have taken place prior to the release of SAs. The analysis is carried out using several statistical models fitted to time series data, including the simple linear regression (SLR), generalised autoregressive conditional heteroscedasticity (GARCH) (1,1) and autoregressive distributed lag (ADL) (1,1) models to estimate abnormal returns and volumes performance. In an additional analysis, the study examines seven factors that may influence the market cleanliness measure and builds on the literature by adding two new factors.

The study provides empirical evidence for the presence of suspicious insider trading activities among the firms listed in the Tadawul over the relevant period where significant abnormal returns and abnormal volumes are observed prior to the arrival of unscheduled announcements. The findings indicate that the level of potential insider trading in the Tadawul, as assessed by market cleanliness measures, is lower after the introduction of

financial reforms. The trading volumes analysis suggests that the decrease in the measures is statistically significant at 10%. However, the returns analysis reveals that the observed reduction is not statistically significant. A possible explanation for this is that the regulatory changes have not yet had a statistically significant effect in reducing the level of potential insider trading activities. Moreover, the lengthy time required for the prosecution procedures and enforcement actions may help interpret insignificant changes in the returns analysis. Further, the literature documents that the efficacy of insider trading laws lies in their efficient enforcement rather than their mere introduction. Moreover, considering that the present study covers the periods preceding and following the entry of foreign qualified investors, the market reactions and investors behaviours may have witnessed changes across the periods examined. Thus, further evidence on insider trading practice in the forthcoming years is needed to have more understanding about the overall impact of the emended regulations.

The study makes several contributions that are of major importance to policymakers, firms and investors. The research satisfies the need to understand the effectiveness of insider trading laws as well as their enforcement in the Tadawul and provides recommendations for how the regulatory agency may determine whether additional regulations are required to improve regulatory performance. The findings may be beneficial in notifying regulators' enforcement mechanisms for strengthening market surveillance and combating market misconduct by more actively implementing disciplinary actions to enhance market efficiency and foster investors' confidence. Apart from this contribution, the results may be of interest to firms seeking to better maintain private information and regulate the release of material-sensitive information through appropriate channels. Finally, the findings may benefit investors by boosting their understanding of market integrity and confidence because the results provide valuable information about market condition and risk.

Declaration

I, Abdulrhman Abdullah Alqurayn, declare that the PhD thesis entitled ‘Assessment of potential insider trading in the Saudi Stock Exchange before and after the introduction of financial reforms: An event study market cleanliness methodology’ 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.

Signature: [redacted] Date: 15 November 2023

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IN THE NAME OF ALLAH, THE MOST GRACIOUS, THE MOST MERCIFUL

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List of Abbreviations

ADL	Autoregressive distributed lag
APAVs	Abnormal pre-announcement volumes
APPMs	Abnormal pre-announcement price movements
ARs	Abnormal returns
ARCH	Autoregressive conditional heteroscedastic
AVs	Abnormal volumes
BHAR	Buy-and-hold abnormal return
CAPM	Capital asset pricing model
CARs	Cumulative abnormal returns
CAVs	Cumulative abnormal volumes
CEO	Chief executive officer
CMA	Capital Market Authority
CMG	Capital market governance
CML	Capital Market Law
CRSD	Committees for Resolution of Securities Disputes
CRSP	Centre for Research in Security Prices
DiD	Difference-in-Differences
DOJ	Department of Justice
DS	DataStream International
EGLS	Estimated generalised least squares
EMH	Efficient markets hypothesis
FCA	Financial Conduct Authority
FSA	Financial Services Authority
FSDP	Financial Sector Development Program
FSMA	Financial Services and Markets Act
GARCH	Generalised autoregressive conditional heteroscedasticity
GCC	Gulf Cooperation Council
IID	Independently and identically distributed
IOSC	International Organization of Securities Commissions

KSA	Kingdom of Saudi Arabia
LM	Lagrange multiplier
LR	Likelihood ratio
M&As	Merger and acquisitions
MAR	Market Abuse Regulation
MCMs	Market cleanliness measures
MCR	Market Conduct Regulation
MDH	Mixture of distributions hypothesis
MDPRD	Market Data Premium Reports Database
MENA	Middle East and North Africa
MM	Market model
MRQ	Main research question
NASDAQ	National Association of Securities Dealers Automated Quotations
NS	Not significant
NYSE	New York Stock Exchange
OLS	Ordinary least squares
RQs	Research questions
RSQs	Research sub-questions
SAs	Significant announcements
SAMA	Saudi Arabian Monetary Authority
SARs	Standardised abnormal returns
SCARs	Standardised cumulative abnormal returns
SEC	Securities and Exchange Commission
SIAH	Sequential information arrival hypothesis
SLR	Simple linear regression
TASI	Tadawul All Share Index
UK	United Kingdom
US	United States
VMCMs	Volume market cleanliness measures
WFE	World Federation of Exchanges

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Chapter 1: Introduction

1.1 Research Background and Motivation

Information on securities markets is a motivating force for the trading operations of market participants. Unlike public information, private information provides a unique advantage for certain market participants, usually corporate insiders, who possess superior access to such information compared with other market participants (Davis et al., 2020; John & Lang, 1991). The impact of private information comes from it being composed of material price-sensitive information. This in turn can incentivise insiders to exploit foreknowledge of their firms' performance and enable them to earn excess returns by engaging in insider trading (Keown & Pinkerton, 1981; Lee, 2021). Insider trading occurs when practitioners trade on the stock exchange based on inside (non-public) information arising from their superior knowledge and hence asymmetrical information advantage (Engelen & Van Liedekerke, 2010; Waxman, 2017; Yin & Zhao, 2015).

A number of prominent scholars in securities law and financial markets have extensively debated whether the potential benefits of insider trading practice outweigh its drawbacks. On the one hand, a vast literature is devoted to the serious harm that insider trading does to capital market fairness, liquidity and stock price informativeness, and thus it requires strict regulations (Bhattacharya & Daouk, 2002; Kwabi et al., 2018; Ojah et al., 2020). On the other hand, another school of thought has argued in favour of insider trading, stating that it fosters market efficiency and is an efficient method to compensate corporate managers for their entrepreneurial efforts (Carlton & Fischel, 1983; Manne, 1966).[1] Despite the long-standing literature debate between the opponents and proponents of insider trading prohibition, illegal insider trading is considered criminal conduct in many countries. As a

[1] It is important to note that not all forms of insider trading are illegal; yet some are entirely legitimate (McGee, 2010; Shell, 2001).

result, most countries have established laws and legislation to prevent market misbehaviour such as insiders abusing their superior knowledge of private information (Bhattacharya & Daouk, 2002; La Porta et al., 2002; Porta et al., 1998).

Investigating the integrity of stock markets has been worthwhile over time and drawn the attention of researchers. Evidence from over three decades of insider trading investigation predominantly supports the assumption that illegal insider trading enables insiders to either gain abnormal profit or avoid potential loss by exploiting their privileged information at the expense of other investors (Barclay & Warner, 1993; Jain et al., 2018; Kyle, 1985; Seyhun, 1992). An extensive body of literature on illegal insider trading documents that financial markets are structured on trust, and that the abuse of the possession of private information prior to public announcements harms that trust and thus raises concerns about market integrity and efficiency (Dalko & Wang, 2016; Monteiro et al., 2007).

Given the significance of integrity within the stock market and its influence on the trust of investors, the prevalence of insider trading activities in the Saudi Stock Exchange (Tadawul) has raised questions about the integrity of the market and the potential for the practice to undermine investors' confidence. In 2018, the Saudi Capital Market Authority (CMA) imposed 129 penalties on 249 violators of rules and regulations. Penalties for insider trading were the highest, totalling more than 86 million USD.[2] In August 2021, the CMA referred a group of more than 250 individuals for public prosecution, charged with disclosing inside information for listed firms on social media.[3] The media have expressed concern over the pervasiveness of insider trading because of abundant rumours circulating within the Tadawul.[4] These are critical issues that could discourage investor participation, influence

[2] https://cma.org.sa/en/Market/Reports/Documents/cma_2018_report.pdf
[3] https://cma.org.sa/en/Market/News/pages/CMA_N_2942.aspx
[4] https://www.reuters.com/article/us-mobily-fine-idUSKCN1GA25N

market liquidity and worsen stock price informativeness (Ahern, 2020; Bhattacharya & Daouk, 2009; Collin-Dufresne & Fos, 2015; Kim et al., 2019).

In contrast to the vast literature investigating insider trading in the United States (US) and other developed capital markets, the Tadawul has received very little scholarly attention. Alkhaldi (2016) examines several insider trading cases in the Tadawul and notes that those cases reviewed by the Committees for Resolution of Securities Disputes (CRSD) did not employ consistent assessment processes. Other research papers address instances of market misconduct in the Tadawul that involve manipulation, poor transparency and insider trading practices, indicating that such misconduct is caused by deficiencies in the regulatory framework and inactive reactions from the regulatory regime (Al-habshan, 2017; Alkhaldi, 2015). In line with latter view, Alomari (2020) scrutinises the lack of clarity present in both legal terminology and judicial precedents pertaining to insider trading regulations in the Capital Market Law (CML).

While numerous studies on the Tadawul focus on the theoretical aspects of insider trading regulation, there is a lack of empirical studies estimating possible insider trading practices in the Tadawul, most of which focus on the stock price reaction and market efficiency. For example, Syed and Bajwa (2018) examine the impact of quarterly earnings announcements on the stock price reaction in the Tadawul and find the existence of significant abnormal returns (ARs) over several days prior to earnings announcements. Felimban et al. (2018) investigate the stock market response to dividend announcements in Gulf Cooperation Council (GCC) countries, including on the Tadawul, and suggest the occurrence of information leakage before announcement dates. In contrast, Alhassan et al.'s (2019) examination of the informativeness of earnings announcements on the Tadawul indicates that stock price reactions to earnings announcements are well behaved because of continuous improvements in regulatory performance.

The CMA though affirms that the CML and its implementing regulations prohibit insider trading practice and consider it as a criminal offence in Saudi Arabia. The Saudi government has taken tremendous steps to develop its economy by implementing financial reform plans, broadly referred to as *Saudi Vision 2030*, which was adopted in 2016. The reform plans were accompanied by a more elaborate program called the Financial Sector Development Program (FSDP). One purpose of the FSDP is to develop effective financial institutions to support the growth of the capital market and qualify the Tadawul as an advanced capital market. Therefore, the CMA has undertaken crucial initiatives that include loosening ownership limits for foreign investors to attract more investors and amending the Market Conduct Regulation (MCR), which involved extending the scope of insider trading prohibition.

However, despite millions of dollars in fines imposed on insider traders along with criminal charges brought against hundreds of individuals implicated in illegal insider trading, the ramifications of the practice have heightened concerns about integrity in the Tadawul and may threaten the aim of attracting more investors. It may be conjectured that insider trading legislation in the Tadawul lacks a sufficient mechanism to deter such misbehaviour. Academic studies show the significance of enforcing insider trading laws and find that legislative effects would be expected when enforcement mechanisms are enforced strictly, not merely by establishment of laws (Bhattacharya & Daouk, 2002, 2009; Cline et al., 2021; Kwabi et al., 2018).

In other words, the low quality of institutions, weak enforcement of insider trading laws and minimal penalties and sanctions may create space for insiders to engage in market misconduct (Dalko & Wang, 2016; La Porta et al., 1999; Porta et al., 1998; Zhang & Zhang, 2018). These are critical challenges that confront securities regulators seeking to maintain market discipline and promote investors participation. The amount of confidence in the market can affect the amount of financing that can be raised through the stock market (Bhattacharya & Daouk, 2002). These problems have motivated this thesis.

The remainder of this chapter is structured as follows. Section 1.2 presents the primary aim of the research alongside its research objectives (ROs). Section 1.3 states the main research questions (MRQs), research questions (RQs) and research sub-questions (RSQs). An overview of the research methodology employed in this thesis is provided in Section 1.4. Section 1.5 provides a brief recapitulation of the study findings followed by the contributions and implications arising from this research in Section 1.6. In Section 1.7, the structure of the thesis is presented through the provision of a synopsis for each chapter. Section 1.8 provides a summary of the content covered in this chapter.

1.2 Research Aim and Objectives

Since the Saudi government instigated its comprehensive financial reform plan, the Tadawul has witnessed fundamental developments and faces ongoing regulatory and institutional changes. The CMA has implemented crucial initiatives aimed at attracting more investors and removed barriers to foreign investment participation. However, the millions of dollars in fines imposed on insider traders and hundreds of individuals charged with violations of the law by leaking inside information and media coverage of abusive behaviour in the Tadawul, have had repercussions for the Tadawul's integrity.

The question at hand pertains to the efficacy of sanctions and monetary penalties as credible deterrents for those who violate insider trading law in the Tadawul. Furthermore, the objective of enticing more investors may encounter obstacles because of prevailing mistrust. Considering that market integrity is impaired, investor confidence is reduced with the consequence of less investor participation as well as threatening the ability to achieve the aims of financial reform plans and their likelihood of success.

Algaeed (2021) suggests that the performance of the Saudi capital market with regard to its contribution and promotion towards economic development remains suboptimal. In their empirical investigation of the impact of governance mechanisms and ownership structure on foreign investor decisions for all non-financial firms listed in the Tadawul in 2019, Bajaher et al. (2022) indicate that recent changes in governance and capital market regulations in Saudi Arabia may not be adequate in terms of inducing institutional foreign investment. It could be argued that the weak governance of capital markets can result in less capital allocation efficiency and raise investor concerns about their investment safety.

The amended regulations introduced with the financial reforms were intended to enhance the confidence of investors, tackle market misconduct and further align market practices with global best practices. However, there is an urgent need to understand more about market abuse in the Tadawul, especially illegal insider trading practice, which has hitherto been the subject of little empirical research. Yet, as far as I am aware, no empirical investigation to date has been conducted on the impact of the financial reforms on potential insider trading in the Tadawul. It is thus the primary aim of this study to fill this gap by investigating the impact of regulatory amendments introduced with the financial reforms on the integrity of the Tadawul, with a particular focus on potential insider trading practice.

The effects of the regulatory amendments implemented as part of the financial reforms on the level of insider trading activities is empirically assessed here by estimating and comparing market cleanliness measures (MCMs) of the Tadawul in two periods: before (i.e., 26 April 2011 to 25 April 2016) and after (i.e., 26 April 2016 to 25 April 2020) the introduction of the financial reforms. The event study market cleanliness methodologies estimate the insider trading level by determining the proportion of significant announcements (SAs) that were preceded by abnormal pre-announcement price movements (APPMs) and abnormal pre-announcement volumes (APAVs), which are more likely to be driven by insider trading activities. To achieve the aim of this thesis, the research pursues the following research objectives (ROs):

1. To estimate the level of potential insider trading based on the returns event study of the market cleanliness measures for all firms listed on the Tadawul in the periods both before and after the introduction of the financial reforms.
2. To examine if the utilisation of several event windows with varying lengths would have a significant impact on the market cleanliness measures between both periods.
3. To investigate the extent to which changes in the market cleanliness measure may be driven by other explanatory variables.
4. To estimate the level of potential insider trading based on the trading volume event study of the market cleanliness measures for all firms listed on the Tadawul in the periods before and after the introduction of the financial reforms.
5. To assess the impact of the financial reforms on the level of potential insider trading in the Tadawul by comparing the difference of the return event study of the market cleanliness measures before and after the introduction of the financial reforms.
6. To assess the impact of the financial reforms on the level of potential insider trading in the Tadawul by comparing the difference of the volume event study of the MCMs before and after the introduction of the financial reforms.

1.3 Research Questions

In view of the primary purpose of the study, this thesis strives to answer the overarching research question of whether the regulatory changes introduced with the financial reforms in 2016 have succeeded in reducing the level of potential insider trading activities in the Tadawul. The main aim of the study is addressed by posing the following main research questions (MRQs):

MRQ$_1$. Is the level of potential insider trading assessed by the MCMs of returns event study significantly lower after the introduction of financial reforms?

MRQ$_2$. Is the level of potential insider trading assessed by the MCMs of trading volume event study significantly lower after the introduction of financial reforms?

The research objectives are addressed by posing the following research questions (RQs) and research sub-questions (RSQs):

RQ$_1$. Is there evidence of SAs wherein firms announcements have a significant impact on the distribution of cumulative abnormal returns (CARs) during the post-event window?

RQ$_2$. Is there evidence of APPMs wherein firms announcements have a significant impact on the distribution of CARs over the pre-event window?

RQ$_3$. Does the use of multiple event windows with varying lengths have a statistically significant impact on the results for the MCMs between the two periods?

RSQ$_1$. Do the stocks return residuals suffer from the presence of heteroscedasticity and serial correlation?

RQ$_4$. To what extent do sample-specific characteristics of the seven factors examined have an impact on the MCMs?

RQ$_5$. Is there evidence of SAs wherein firms announcements have a significant impact on the distribution of cumulative abnormal volumes (CAVs) over the post-event window?

RQ$_6$. Is there evidence of APAVs wherein firms announcements have a significant impact on the distribution of CAVs over the pre-event window?

RSQ$_2$. Do trading volume data suffer from the existence of heteroscedasticity and serial correlation?

RQ₇. Is there a relationship between the MCMs of the return and volume analysis wherein the SAs that were accompanied by APPMs were also accompanied by APAVs?

1.4 Overview of the Market Cleanliness Methodology

This section provides the underlying meaning and contextual background for the event study market cleanliness methods. The key intuition of MCMs specifically revolves around the identification of abnormal price movements and abnormal trading volumes that have taken place prior to the disclosure of corporate news. Conceptually, the rationale behind MCMs is the simple notion which supposes that in a clean market, asset behaviours react immediately when announcements are made public. Conversely, in an unclean market, the substantial abnormal movements that occur ahead of corporate news announcements are more likely to be motivated by suspicious trading. For example, if share prices increase significantly, in the case of good news, and unlike normal stock behaviour in the days leading up to the announcement date, such movements can be indicative of information leakage about the event and can signal that insider trading is occurring.

Research has yielded significant findings about the association between insider trading activities and their impact on the movements of stock returns and trading volumes patterns. Scholars and multilateral organisations attribute that the run-ups of large ARs or abnormal volumes (AVs) observed prior to major events of price-sensitive information are viewed as an indicator that an announcement includes significant news about a share's value and can be a signal of insider trading practices (Augustin et al., 2019; Cheong et al., 2022; Collin-Dufresne & Fos, 2015; Davis et al., 2020; Goldman et al., 2014; Jaffe, 1974; Jagolinzer et al., 2020; Olmo et al., 2011; Seyhun, 1986).

It has been empirically documented that the market can detect insider trading activity because such practice impounds information into the stock price (Bhattacharya et al., 2000;

Meulbroek, 1992). For example, drawing on firsthand observations of insider trading incidents, Meulbroek (1992) reveals interesting results pertaining to 183 illegal insider trading cases charged by the US Securities and Exchange Commission (SEC) from 1980 to 1989. The author discovers that 43% of price run-ups are observed over the 20 days before takeover announcements. In a similar vein, Ahern (2017) examines insider trading prosecutions filed by the SEC and the Department of Justice (DOJ) of the US between 2009 and 2013. The author reports that the stock return average of trading on inside information gains 34.9% over the 21 trading days from the original leakage date up to the official public announcement of regulatory announcements and merger and acquisitions (M&As) events yield average returns of 43.0% over the 31 trading days leading up to the event date. Similarly, Augustin et al. (2019) estimate that 25.0% of M&As are preceded by illegal insider trading. These findings provide empirical evidence of the impact of insider trading on the process of security price formation.

From a methodological point of view, the MCMs employed in the present study is underpinned by market efficiency theory. The pioneer of the efficient market hypothesis (EMH), Fama (1970), states that an efficient market is one in which stock prices reflect all available information. According to Clarke et al. (2001), 'If markets are efficient and security prices reflect all currently available information, new information should rapidly be converted into price changes' (p. 15). Nonetheless, some researchers have argued that insider trading activities are useful for market efficiency because such trading activities enable information to be quickly integrated into stock prices. Arguments around market efficiency alongside other areas of disagreement surrounding the benefits and harms of insider trading practices are discussed in depth in Chapter 3.

In Interpreting the presence of abnormal assets movements before the release of corporate news in the context of the EMH, the inclusion is that it violates the strong form of the EMH, which suggests that asset prices reflect all public and private information. According to Fama (1970), 'strong form tests concerned with whether given investors or groups have monopolistic access to any information relevant to price formation' (p. 383). Having discussed the theoretical framework for MCMs, the structure and calculation of the MCMs used in this study is explained in more detail in the following section.

1.4.1 Calculation of the Market Cleanliness Measure

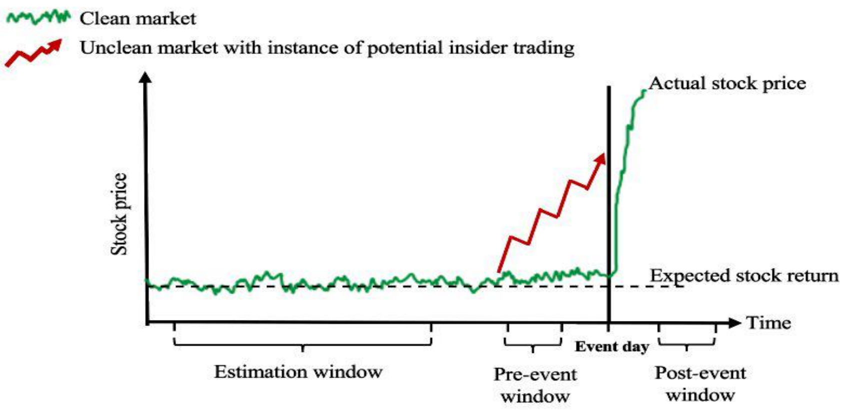
Figure 1.1 illustrates how insider trading activities might impact price movements and describes the fundamental aspects required for the calculation of the MCMs. The explanation here focuses on the returns-based event and volume-based event studies explained in Chapter 5 (see Section 5.7).

In an efficient market, it is assumed that a firm's share price will show an immediate reaction on the day of an announcement conveying price-sensitive news. Likewise, in a clean market, as shown by the green line in Figure 1.1, asset price movements follow normal behaviour in the absence of new information over the estimation window leading up to the official announcement date. Once the announcement is made publicly, as indicated by the vertical line labelled as the event day, the stock price reacts instantly, showing a clear spike on the event day because of the arrival of good news. A plausible explanation for this pattern is that in the case of a price-sensitive announcement, the information arrival drives changes in price in bunches rather than being equally spaced over time.

However, in an unclean market, as represented by the rising red arrow in Figure 1.1, stock price movements begin an upward drift, as shown by the rising red line, several days before the event day during the pre-event window and in the same direction of overall price movements. Although the news announcement has not been published during this period, the asset price enjoys a significant increase in advance of the event day, which can yield a positive AR. Thus, it is likely that trading based on non-public information has taken place before the release of the SA. This pattern is a signal of a leakage of information about the event and could be indicative of instances of potential insider trading activities. Therefore, by measuring this pattern, APPMs can be estimated.

Figure 1.1

Key Indicator of Market Cleanliness



The MCMs can be measured using the ratio of APPMs observed before SAs. Section 5.4.3 describes techniques used to determine if an event is a SA and preceded by APPM. Briefly, significant CARs over the post-event window imply that the announcement contains important news and should be considered a SA, while significant CARs across the pre-event window are an indicator of the occurrence of APPMs. In contrast, an event is not considered a SA or preceded by an APPM if no statistically significant CARs are detected over the event window being examined.

1.4.2 Motivation for Employing the Market Cleanliness Measures

Having described the methodology employed in this thesis, it is worth explaining the motivation for utilisation of this approach. While Section 4.2.3. provides extensive justification in this regard, the reasons for employing this methodology can be concisely summarised as follows. First, MCMs have been applied in academic and regulatory settings as an indicator of the level of possible insider trading activities (Australian Security &

Investments Commission [ASIC], 2016, 2019; Dubow & Monteiro, 2006; Goldman et al., 2014; Monteiro et al., 2007).

For instance, the United Kingdom (UK) Financial Conduct Authority (FCA) (formerly the Financial Services Authority [FSA]) employs MCMs to examine the influence of the *Financial Services and Markets Act* (FSMA) on the level of insider trading before and after the enforcement of the FSMA. The FCA has conducted several market cleanliness studies for firms listed on UK securities markets and published annual updates to the MCMs over the last two decades (Dubow & Monteiro, 2006; Goldman et al., 2014; Monteiro et al., 2007). Similarly, the ASIC (2016, 2019) has applied MCMs to assess the cleanliness of Australian equity markets after the transfer of market supervision.

The Saudi government in 2016 launched a financial reforms plan that led the CMA to implement considerable restructuring decisions and regulatory changes with the aim of improving the capital market environment. Thus, MCMs are highly pertinent to the main aim of the current study as their use serves as an efficient method for evaluating the influence of the new legislation associated with financial reforms on the level of potential insider trading practice.

Second, the approach is considered a measure of whether insider trading rules and fair disclosure are complied with. According to Carvajal and Elliott (2009), ‘Market cleanliness studies measure the whole effect of a compliance program, not only of the enforcement (sanctioning) function’ (p. 32). The authors note that such studies provide important insights into the effectiveness of enforcement mechanism of securities regulation.

Third, the approach provides a foundation for tracking the deterrent effect of new regulation in a regulatory setting in relation to insider trading activities and corporate disclosure. MCMs can be used to estimate the statical significance level of SAs, APPMs and APAVs by using the well-known event study method. According to Bodie et al. (2019)

evidence of information leakage can broadly be detected by event studies indicating potential violations of insider trading regulations. Further information on the event study approach is provided in Section 4.3.

This thesis presents four empirical works undertaken to address the research questions and test their related hypotheses. The study performs a returns-based event study approach by utilising two market cleanliness methods based on daily data observations. The first returns event study pertains to the conventional MCMs (see Section 5.4). The second is based on the advanced MCMs (see Section 5.5). The third empirical part is carried out using logistic regression models to investigate seven specific factors that may affect the MCMs, as outlined in Section 5.6. Fourth, the study undertakes a volumes event study using daily trading data, as described in Section 5.7. The analysis is conducted using a variety of econometrics models that include simple linear regression (SLR), generalised autoregressive conditional heteroscedasticity (GARCH) (1,1), autoregressive distributed lag (ADL) (1,1), and ADL-GARCH for modelling ARs and AVs to assess the effectiveness of the models, examine their differences and draw meaningful conclusions.

1.5 Key Findings of the Research

After providing a brief description of the methodology utilised in this thesis, this section briefly summarises the key findings of the study. The empirical analyses conducted in this study endeavour to present a systematic and comprehensive assessment of potential insider trading in the Tadawul before and after the introduction of financial reforms by utilising the event study market cleanliness methodologies. The RQs were examined using a sample consisting of 1,958 unscheduled announcements from all firms that were listed in the Tadawul and made announcements over the relevant period (i.e., 26 April 2011 to 25 April 2020), alongside data on daily stock prices and daily trading volumes.

Throughout the relevant period, the study provides evidence of SAs where ARs and AVs exist around firms announcements days. The study provides evidence of events for which APPMs and APAVs were observed prior to the release of SAs. The study reveals the proportion of APPMs and APAVs detected prior to SAs over the relevant period. Generally, the findings indicate that the level of potential insider trading estimated by the returns and volumes event study market cleanliness measures are lower after the introduction of financial reforms. However, the observed drop in returns analyses do not permit a rejection to the relevant null hypothesis because the difference for the subsequent period was not statistically lower than the preceding period. In contrast, the trading volume analysis fails to reject the related null hypothesis considering that the observed reduction following the introduction of financial reforms is statistically significant at 10%.

Regarding the investigation of the utilisation of several event window lengths, the outcomes show that variation in the MCMs between the two periods (i.e., pre- and post-financial reforms) is insignificant regardless of the length of the event window. As for the examination of whether the changes in MCMs might be influenced by other explanatory factors, the results suggest that, with the exception of one factor—namely trading activity—none of the other variables have a significant impact on the MCMs.

1.6 Contribution to Knowledge and Statement of Significance

This study is motivated by several streams of research. First, there is a need to understand the effectiveness of insider trading prohibition laws and credible deterrence enforcement because of increasing concern about the prevalence of insider trading activities in the Tadawul. Second, there is a need to understand what impact financial reforms have and whether new regulations have succeeded in reducing potential insider trading activities in the Tadawul. Third, the study fills a gap pertaining to the scarcity of empirical framework research on the Tadawul; in particular, illegal insider trading. This research provides recent evidence of insider trading practice by utilising the tools of empirical research that can address the issue in a more pragmatic way, which provides practical support to studies on the theoretical background and contributes to a better understanding of the issue being examined from different directions.

This study makes several contributions to the literature and body of knowledge. The impact of the financial reforms conducted by the Saudi government in 2016 on insider trading, to the best of the author's knowledge, has not been empirically examined. Therefore, this study seeks to contribute to current empirical knowledge by empirically investigating the impact of financial reforms on the level of possible insider trading activities in the Tadawul before and after the introduction of the financial reforms. This research may be the first to measure the market cleanliness level of the largest capital market in the Middle East and North Africa (MENA) over the relevant period by providing systematic evidence of potential insider trading activities.

Most studies conducted on the Tadawul have different aims from the present study, do not employ the same method, refer to a different period and use a different data sample. This research is carried out in various ways that go beyond the scope of previous studies on the Tadawul. For example, as early pointed out to the research papers which investigate the stock prices reaction prior to quarterly earnings announcements as per Syed and Bajwa (2018) and Alhassan et al. (2019) and dividend announcements by Felimban et al. (2018), these types of announcements are often prescheduled earlier. Therefore, one may argue that the presence of significant ARs or AVs before such events is motivated by informed trading of sophisticated investors that is driven by their information acquisition and/or information provision by sell-side analysts (Chen et al., 2020; Weller, 2018). Additionally, such announcements are often subject to explicit insider trading embargoes (Cohen et al., 2012). Besides, the existence of ARs or AVs ahead of the aforementioned types of announcements could be attributable to attentive trading on the basis of public information (as shown by Alldredge & Cicero, 2015) or to the fact that the market is mostly aware of the imminent release of earnings and dividends announcements.

Unlike in previous studies, such firms announcements are excluded from the current study, and the sample here is restricted to include unscheduled firms announcements published by issuers. The justifications for restricting the sample selection to unscheduled announcements is that they are unlikely to be anticipated but are typically known by corporate insiders. Moreover, these announcements are likely to be surprise events to the market assuming that they specifically involve the release of information where the timing is not publicly known, and not easily predictable by market participants. Furthermore, the occurrence of ARs and AVs ahead of unscheduled announcements is more likely due to insider trading activities or other forms of suspicious trading practices that rely on material non-public information and harm the welfare of other market participants (Dai et al., 2016).

Besides, this research employs both analysis of trading volume and stock price event studies, utilises different statistical analyses, uses a distinct type of major events and more recent datasets during a period marked by substantial transformation in the history of the Tadawul. The present study builds on previous studies by examining two new factors that may influence MCMs. Market cleanliness studies such as Dubow and Monteiro (2006), Monteiro et al. (2007) and Goldman et al. (2014) examine a number of factors that may impact measures of market cleanliness, including firm size, volatility and liquidity of the stock, firm innovativeness, the extent of the actual size of the CARs over the event window and industry dummy variables.

This research contributes to the finance literature by including two additional factors—namely, information asymmetry and trading activity—to examine the extent to which changes in these factors may impact measures of market cleanliness. Significant changes in information asymmetry define insiders ARs (Wu, 2019). Felimban et al. (2018) suggest that the response to new information in trading volume activity varies due to the diverse sources of information accessible to investors and the varying levels of accuracy in their private prior information. Further, an issue that may affect the event study method when estimating ARs and AVs is overlapping events. This relates to the case in which a company discloses multiple major events on different days within the estimation window. The present study introduces an event adjustment procedure to handle the effects of overlapping events (see Section 4.3.2).

1.6.1 Statement of Significance (Practical Contributions)

This research presents empirical findings with important implications for policymakers, firms and investors. First, the findings may be beneficial in driving regulators' enforcement mechanisms for strengthening market surveillance and combating market misconduct by more actively implementing disciplinary actions. In addition, sequential reviews and assessments have been called for since the launch of *Saudi Vision 2030* to ensure the delivery of its financial reform plans. Apart from its policy implications, the study is of interest to policymakers as it offers a foundation for regulatory bodies to determine whether additional regulations are needed to strengthen regulatory performance and promote market discipline.

Second, the results may be of interest to firms seeking to ensure proper functioning to accurately maintain material-sensitive information and regulate its release through appropriate channels. The results alert firms of the need to abide by CML rules and adhere to disclosure and transparency policies. Third, investors can benefit from the study as it supplies useful information about market conditions regarding insider trading practices. The research also adds theoretical insights and an understanding of the issues addressing insider trading practices and holds value adding in the emerging market context as well.

1.7 Thesis Structure

This thesis is organised into seven chapters including this introductory Chapter 1. Chapter 2 presents an overview of the regulatory framework and enforcement mechanisms pertaining to insider trading practice in the specific setting of Saudi Arabia. While the chapter broadly discusses the evolution of the Tadawul since its beginnings, it specifically sheds light on aspects concerned with insider trading laws. The chapter discusses the regulations of insider trading, the measures and sanctions imposed by regulatory bodies and the practical enforcements in place. It also reviews criticisms in the academic literature aimed at the legal system.

Chapter 3 provides an extensive review of insider trading practices and addresses key points associated with the most contentious areas of disagreement between the opponents and proponents of insider trading regulations. The chapter discusses theories related to insider trading, including agency theory and market efficiency theory. The chapter encompasses numerous studies undertaken at a global scale and provides empirical and theoretical evidence on the significant effects of insider trading.

Chapter 4 draws on pertinent academic studies that prove the role of securities laws in promoting the growth and development of financial markets. This is followed by a review on a supplementary dimension of securities laws, with a particular emphasis on the significance of regulations and enforcement mechanisms pertaining to illegal insider trading practice. The chapter reviews the methodologies and approaches used by researchers in the finance literature when examining the impact of insider trading on stock prices and volumes.

Chapter 5 provides a comprehensive explanation of the research methodology, the sample selection and study period. The chapter demonstrates and justifies the empirical approach employed in this study as well as the appropriateness of particular statistical models and tests to examine the research hypotheses.

Chapter 6 attempts to answer the research questions by presenting empirical findings on the MCMs of the Tadawul throughout the relevant period. The chapter presents empirical evidence from the returns and volumes event studies. Further, the chapter reveals the results of an additional econometric analysis conducted for a further robustness check to draw more meaningful conclusions and ensure that the results are not driven by other explanatory variables.

The thesis concludes with Chapter 7 by revisiting the research objectives and hypotheses alongside discussing the study findings. The implications arising from this research and its limitations, as well as suggestions for future research, are presented in this chapter. References follow this final chapter.

1.8 Chapter Summary

This chapter introduces the thesis by providing background to the topic and outlining the fundamental aspects of the study in terms of the research problem and reasons for the selection of this subject, alongside the motivations that drove the formulation of the research objectives and the research questions. The chapter provides a concise overview of the research methodology and underlying motives that led to the utilisation of the employed methodology. The chapter provides a brief summary of the research findings and contributions to knowledge.

Chapter 2: The Saudi Stock Exchange and Insider Trading Regulations

2.1 Introduction

Prior to delving into the details of the present study, it is useful to provide background information on the Tadawul. This chapter starts by providing a synopsis of Saudi Arabia's economy followed by a summary of the historical evolution and regulatory framework of the Saudi stock market from its beginnings until modern times. This is useful for an understanding of the regulatory environment concerned with insider trading in the Saudi context. Thus, this chapter offers a comprehensive overview of the insider trading legislation in Saudi Arabia, tracing its origins and development within the historical, societal and regulatory framework. Additionally, the amendments and measures employed by regulatory bodies regarding insider trading regulations and their practical enforcement are presented.

The remainder of this chapter is organised as follows. In Section 2.2, a concise background to the country's economic landscape is presented, along with a comprehensive account of the historical evolution and progression of the Tadawul. Section 2.3 presents a background to the legal structure governing the prohibition of illegal insider trading practice in Saudi Arabia. Section 2.4 reviews academic studies of insider trading regulations in the context of Saudi Arabia and highlights enforcement actions taken by regulatory bodies in response to such market abuse. Section 2.5 concludes this chapter by summarising the key points reviewed throughout the chapter.

2.2 Evolution of the Tadawul

The Kingdom of Saudi Arabia (KSA) is economically one of a few fast-growing countries in the world. Its economy is in of the world's top 20 and the largest in the Arab world and Middle East.[5] The KSA has a globally established presence and is already a considerable player on the world stage because it is well known that the country plays a pivotal role in relation to the oil market. In addition to the progress achieved in the development field over the past decades, later in April 2016, the KSA's government has sought to move towards launching a concerted comprehensive economic transformation and diversification by adopting the *Saudi Vision 2030*, which essentially consists of financial reforms to boost the diversification of the country's economy.

Accordingly, the Tadawul has witnessed a rapid transformation in recent years. Over the past two decades, it has become considerably more attractive to investors; especially because the regulatory body has driven ongoing regulatory improvements to advance the Tadawul's development and growth. The Tadawul ranks ninth in terms of size among the 67 members of the World Federation of Exchanges (WFE). Additionally, it holds a dominant position in the GCC market, and is ranked third in size among its emerging market counterparts. The Tadawul is a member of several prominent organisations including the International Organization of Securities Commissions (IOSC), the WFE and the Arab Federation of Exchanges.[6] According to the WFE, the Tadawul is the world's tenth largest market with a market capitalisation of 3,085,233.11 million USD as of November 2023. Table 2.1 provides an overview of the key indicator activities during the period covered by this study.

[5] https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?most_recent_value_desc=true&year_high_desc=true
[6] https://www.tadawulgroup.sa/wps/portal/tadawulgroup/portfolio/saudi-exchange

Table 2.1

Key Indicators of the Saudi Stock Exchange Activity from 2011 to 2020.

Year	Listed Firms	Value Traded (in Million SAR)	Market Capitalisation (in billion SAR)	No. of Transactions	Volume Traded (in million)
2011	150	1,098,836.75	1270.48	25,546,933	48,263.74
2012	158	1,929,318.27	1400.34	42,105,048	83,401.88
2013	163	1,369,665.79	1752.86	28,967,694	55,561.35
2014	169	2,146,511.90	1812.89	35,761,091	72,908.20
2015	171	1,660,622.05	1579.06	30,444,203	70,826.18
2016	176	1,156,987.08	1681.95	27,273,685	70,630.26
2017	179	836,275.13	1689.60	21,895,281	47,401.05
2018	190	870,869.68	1858.95	25,011,885	41,004.31
2019	199	880,139.07	9025.44	28,395,793	35,831.89
2020	203	2,087,799.41	9101.81	76,686,329	81,588.20

Source: Statistical Bullet of the CMA annual report. The prevailing exchange rate between the USD and the SAR is roughly 3.75.

Recently, the Tadawul has witnessed substantial evolution as shown in increased participation of international investment entities. The CMA as the sole regulator of the Saudi capital market has removes barrier to foreign qualified investors, with subsequent inclusion of the Tadawul in leading providers of global equity indices. For instance, in 2015, the Tadawul opened its stock market to foreign investments, attracting hundreds of millions of dollars in foreign cash; in fact foreign investment rapidly jumped specifically in the first quarter of 2019.[7] Additionally, one of the radical progressions in the Tadawul's history is its inclusion in 2019 in major international indices: the Financial Times Stock Exchange (FTSE Russell), S&P Dow Jones and Morgan Stanley Capital International (MSCI) emerging markets indices.[8]

Although shares trading began in Saudi Arabia as early as the 1930s, the Saudi stock market remained an informal institution until the mid-1980s. Due to steep growth in the number of joint stock firms, an unofficial stock market emerged as early as the 1980s. Later,

[7] https://www.bloombergquint.com/business/saudis-issue-70-more-foreign-business-licenses-from-year-ago
[8] https://www.reuters.com/article/us-saudi-aramco-ipo-indexes/msci-sp-dow-jones-ftse-russell-could-fast-track-aramco-into-indices-idUSKBN1XP23Q

in 1984 a ministerial committee was tasked by the Saudi government to establish the Saudi Share Registration Company with the aim of developing and regulating the stock market and bringing all stock trading activities under the supervision of the Saudi Arabian Monetary Authority (SAMA).[9]

Share ownership was based on a physical documentation system until 1990, when the SAMA launched an electronic trading system called the Electronics Securities Information System (Ramady, 2010). This marked the beginning of a new period in the construction of a framework for electronic share trading in Saudi Arabia. Subsequently, the sophisticated automatic trading system known as the Tadawul was launched in 2001, facilitating trade processed via the Internet and resulting in the emergence of a new stock market index named the TASI (Tadawul All Share Index). There are two other indices in the Tadawul: the Saudi Parallel Market (Nomu) launched in 2017 and the MSCI Tadawul 30 Index, which was included in 2018.[10] [11]

The TASI tracks the performance of all firms listed on the Tadawul and is currently registered as the official Saudi stock market index. The system delivers an effective, precise and rapid settlement. According to Ramady, 'as of 2004, the Saudi stock market trading system became one of the most technologically advanced system in the world, with T + Zero delivery-transaction plus zero days' (p. 149). The establishment of the Tadawul as a joint stock company was formally passed by the Council of Ministers in March 2007.

In the two decades following formal establishment of the Saudi stock market, a further regulatory change occurred when a new CML, comprising 67 articles, was approved by the Council of Ministers, in June 2003. The new law creates an independent Saudi

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[9] It is noteworthy that in November 2020, the SAMA changed its official name change to become the Saudi Central Bank. However, the organisation opted to maintain its original acronym, SAMA, in recognition of its longstanding historical significance both domestically and abroad. The news is available at https://www.sama.gov.sa/en-US/News/Pages/news-629.aspx

[10] https://cma.org.sa/en/MediaCenter/PR/Pages/msciincljune2018.aspx

[11] https://www.msci.com/eqb/methodology/meth_docs/MSCI_Tadawul_30_Index_Mehodology_Dec2018.pdf

Arabian SEC, currently known as the CMA. The law introduced new rules to enhance disclosure and transparency, protect investors' interests and address some of the shortcomings in the older rules with stronger capital market regulations.

2.3 Regulations of Saudi Law Relating to Illegal Insider Trading Practice

During the last two decades of the twentieth century, the regulation and control of insider trading was not a well-established practice in the Saudi stock market's history and several recent studies centring on governance and transparency matters indicate that there remains a pressing necessity for additional regulations (Al-habshan, 2017; Alkhaldi, 2016; Bajaher et al., 2022). Indeed, prior to 1997, directors of listed firms could legally trade on inside information about their companies without breaching any laws, as there was no legislation restricting corporate insider from conducting such practice.

At that time, the only relevant law in force was the *1965 Law of Companies*, which was not sufficiently successful in regulating insider trading in the market (Alkhaldi, 2016).[12] Its Article 72 states that the board of directors should not disclose secrets about the company to shareholders or third parties outside the general assembly meeting. Article 134 states that it is impermissible for auditors to reveal what they know of a company's secrets to shareholders or third parties outside the general assembly meeting.

It should be noted that the 1965 law only forbids auditors and directors from disclosing private information; neither of these two parties who could attain sensitive information are prohibited from disclosing such information. More critically, there are no statements in the law preventing directors utilising their privileged access to inside information from their own firms. Also, neither auditors nor any other persons are prohibited from trading based on non-public information.

[12] https://www.idc.gov.sa/en-us/RulesandRegulations1/The%20saudi%20Companies'%20Law.pdf

Subsequently, the SAMA—which, as mentioned above is responsible for market surveillance—issued in 1990 supplementary regulations about insider trading practices preventing employees of banks who process buying/selling shares orders from trading based on unpublished information. Despite extending the scope of restrictions compared to prior rules, by including new parties in addition to directors and auditors, the updated legislation still lacks a strong restriction concerning insider trading regulations.

A wider framework, the Disclosure Rules was issued in 1997 by the Ministerial Committee that prohibits, for the first time ever, all insider trading activities for all market participants. Nevertheless, the 1997 Disclosure Rules fail again in amending insider trading legislation effectively because sanctions for violations are not included, although any breach of the law will be subject penalties by the government (Alkhaldi, 2016). The rules only state that, 'the creation of an unfair market and/or person acting on inside information is prohibited'.

Al-Suhaibani and Kryzanowski (2000) conducted an empirical study to examine the information content of an order submitted on the Tadawul from 1996 to 1997 and note that large and more aggressive orders are more informative. Their findings show that insider trading on the Tadawul is probable because there is no efficient mechanism in place to hinder insiders from trading on inside information. Nonetheless, these outcomes were derived from data that are more than two decades old. Things have changed, and it remains unclear if such practice is still prevalent.

All in all, the most comprehensive and judicial regulatory actions in the Tadawul's history are those recently adopted by the Saudi government. The CMA, an independent financial and administrative authority, was formally established in July 2003 under the current CML and pursuant to *Royal Decree No (M/30)* with the aim of regulating and developing the Saudi Arabian capital market, maintaining investor confidence and ensuring equitable practices for all participants in the market by issuing the rules and regulations required to implement the provisions of the CML. In March 2021, the Saudi Exchange is a wholly owned subsidiary by Saudi Tadawul Group after Tadawul was converted into a holding company named Saudi Tadawul Group Holding Co.[13]

The CMA declares that, 'the basic objectives are to create an appropriate investment environment, boost confidence, and reinforce transparency and disclosure standards in all listed companies, and to protect the investors and dealers from illegal acts in the market'.[14] The CRSD, which has the jurisdiction statute, was established in accordance with Article 25 of the CML. The CRSD specialises in settling security market disputes that fall within the scope of the provisions of the CML, its implementing regulations and regulations of the authority and market.[15]

Disclosure and transparency levels have grown in the Tadawul and the deficiencies of insider trading regulations in previous laws seem to have been addressed by the relevant authorities. The CMA, however, continues to make improvements to address the regulatory challenges. It has the primary responsibility for preventing deceptive practices and maintaining confidence in the Saudi capital market. Among its duties with respect to insider trading is to 'protect investors and the public from unfair and unsound practices involving fraud, deceit, cheating, manipulation, and inside information trading'.[16]

Under the CML, insider trading is prohibited in the Saudi capital market, and is deemed a criminal activity. The penalty for insider trading practice, which is controlled by the Saudi Public Prosecution, extends to imprisonment. Under Chapter Eight of the CML, 'Manipulation and Trading based on Inside Information', Article 50 stipulates that insider

[13] https://www.tadawulgroup.sa/wps/portal/tadawulgroup/portfolio/saudi-exchange?locale=en
[14] https://cma.org.sa/en/Awareness/Pages/Regulations.aspx
[15] The CRSD is a quasi-judicial financial commission whose primary function is to safeguard the interests of stock market participants and investors in publicly traded companies, enforce rules, maintain market confidence and resolve disputes based on the CML. The CRSD assesses a wide range of cases pertaining to the corporate sector law including instances of illegal insider trading.
[16] https://mep.gov.sa/en/Pages/CapitalMarketAuthority.aspx

trading is prohibited for any person who obtains inside information, by means of family ties, a business or a contractual relationship (referred to as the insider person), to directly or indirectly trade in the security to which this information is related or disclose it to another person expecting such person will trade in that security.[17]

As part of the CMA's efforts to refine the market, enhance the confidence of investors and support participants in avoiding violations of the law, one year after its establishment the CMA issued the MCR, taking effect from November 2004. The MCR was issued with supplemental details concerning abuses in the market including insider trading regulations, and the CMA conducts periodic updates on the rules of the MCR. First, an amended regulation was issued according to a resolution of the CMA Board dated 4 January 2016. More recently, the CMA has put in place a similar procedure by publishing a commentary on market misconduct. The second amendment was issued on 26 January 2021 in accordance with the resolution of the CMA Board.

Article 50 of the CML states that the MCR has set aside a whole chapter for insider trading practice. Chapter 3 of the CML defines the concepts of disclosure and trading based on inside information and confirms that such activity is prohibited, and that perpetrators will be subjected to legal action. Based on the CML, Article 4 of the MCR requires that a security associated with inside information must be a traded security whose value would be materially affected if the information was disclosed or made available to the public. Trading is considered insider trading whether it occurs directly or indirectly in a security related to internal information.

According to Article 4 of the MCR, in two circumstances a person is considered a direct trader: (1) if they proceed a trade in the security for any account in which they have an interest; or (2) if they make a bid or offer on the exchange for the security. In three situations

[17] https://cma.org.sa/en/RulesRegulations/CMALaw/Pages/default.aspx

a person is considered an indirect insider trader: (1) if they execute a trade as an agent for another person; or (2) if they organise a trade in which one of the parties is a relative or a person with whom they have a business or contractual relationship; or (3) if they arrange for their agent or any other person who acts on their behalf or based on his directions to trade in a security related to inside information.

As this study employs the market cleanliness method frequently employed by the FCA of the UK, it is worthwhile describing UK insider trading regulations. Insider trading is considered a criminal offence in the UK. Its FCA describes insider dealing under Article 8 of the Market Abuse Regulation (MAR) as:

> (i) in the circumstances described in (b), he deals in securities that are price-affected securities in relation to the information; (ii) (A) he encourages another person to deal in securities that are (whether or not that other knows it) price-affected securities in relation to the information, knowing or having reasonable cause to believe that the dealing would take place in the circumstances mentioned in (b); or (B) he discloses the information, otherwise than in the proper performance of the functions of his employment, office or profession, to another person; (b) the circumstances referred to in (a) are that the acquisition or disposal in question occurs on a regulated market (identified in an order made by the Treasury), or that the person dealing relies on a professional intermediary or is himself acting as a professional intermediary.[18]

Going back to Saudi laws, it is notable that sequential regulations and their refinements are indicators that the Saudi regulatory body has become stricter in the matter of market misconduct, particularly insider trading. In practice, the CMA in 2018 issued 129 penalties against 249 violators of rules and regulations; insider trading penalties were top

[18] https://www.handbook.fca.org.uk/handbook/MAR/1/3.html#

among the overall financial penalties, with a value of more than 86 million USD.[19] Further, the CMA in August 2021 made a referral of a group consisting of over 250 individuals to the Public Prosecution office. The individuals were charged with the act of disclosing inside information for listed firms on social media. The prevalence of insider trading in the Tadawul has received major coverage in the media owing to numerous news articles circulating within the Tadawul's financial community regarding this market abuse.

The occurrence of such market misbehaviour may indicate that the Tadawul's insider trading legislation remains deficient in terms of deterring such unethical conduct. To clarify, inadequate institutional standards, ineffective implementation of regulations against insider trading and lenient disciplinary measures may provide opportunities for insiders to partake in illegal activities in markets and discourage the participation of outsider investors. In their empirical investigation of the impact of governance mechanisms and ownership structure on foreign investors' decisions for all non-financial firms listed in the Tadawul in 2019, Bajaher et al. (2022) show that recent changes in governance and capital market regulations in Saudi Arabia may not be adequate in terms of inducing institutional foreign investment. Further, Sharif (2019) indicates that the lack of significant advances on the Tadawul after opening markets for qualified foreign investors could be attributed to deficiencies in investor protection rules.

As we shall see in Section 4.2, numerous scholarly studies demonstrate the importance of a high-quality legal system coupled with rigorous enforcement of regulations. Before discussing the significance of regulation alongside the stringent enforcement approach, the section that follows concentrates on enforcement mechanisms with a particular emphasis on those implemented in the Tadawul.

[19] https://cma.org.sa/en/Market/Reports/Documents/cma_2018_report.pdf

2.4 The Enforcement Regime in the Tadawul

Effective misconduct surveillance alongside regulation enforcement are key to not only reinforcing market discipline but deterring illegal practices and holding individuals and entities responsible. Carvajal and Elliott (2009) emphasise the value of enforcement as an influential approach for deterring market abuse. They identify three fundamental factors in securities regulation: the legal framework, the supervision program and the enforcement mechanism. The authors say that supervision aims to hinder violation of the regulations, while enforcement aims to identify and penalise breaches.

Going back to the regulatory framework for insider trading in Saudi Arabia, the literature provides relevant explanations. For example, Alkhaldi (2016) states that regulation depends on a web of articles from the CML and MCR that define insider trading in terms of business, contractual relationships and family; however, these subparts are poorly defined compared with legislation that considers more prudent procedures, such as that in the US where federal statutes and a series of judicial guidelines developed by the US Supreme Court clearly articulate the practice.

Further, Alkhaldi (2015) and Al-habshan (2017) demonstrate instances of market misconduct in the Tadawul. These instances pertain to manipulation, making incorrect statements, insider trading activities and inadequate transparency and disclosure procedures on the part of issuers. Likewise, Altwayan (2019) conducted a comparative analysis with a focus on similarities and differences in regulation of corporate insider trading between the US and KSA, concluding that regulations relating to insider trading in the KSA are somewhat ambiguous compared with those in the US. On this basis, the author suggests that further reform is necessary to the regulations concerning corporate insider trading.

In line with this view, Alomari (2020) scrutinises the lack of clarity present in both legal terminology and judicial precedents pertaining to insider trading regulations in Saudi law. The author offers a critique of the legal definition of insider information with specific emphasis on the difference between ‘use’ and ‘possession’, indicating that the central issue is ambiguity around whether the prohibition applies to engaging in trading activities based on material non-public information or engaging in trading activities while possessing such information.

Beyond the scope of regulatory frameworks that primarily concentrate on insider trading regulations, several studies indicate a necessity for enhancing governance (Bajaher et al., 2022). In their empirical study of non-financial information disclosure in corporate reporting, Alshiban and Al-Adeem (2022) utilise a sample of firms affiliated with three major sectors in the Tadawul that account for 85.51% of the Saudi market capitalisation and find that companies give less attention to the disclosure of information pertaining to environmental matters. Considerations of human rights, bribery and anti-corruption measures are overlooked to a certain degree. Although the sample size is confined to only three sectors, the authors indicate that the disclosure level has remained consistent since 2012 without notable progress.

Having discussed certain deficiencies in the legal framework governing insider trading regulation, another significant aspect that should be considered is the enforcement mechanism and its strength in preventing illegal activities. Maug et al. (2008) analyse a large dataset of 19,000 acquisition announcements from 48 countries to examine how insider trading laws and subsequent enforcement of these laws affect the way in which information related to acquisition announcements leaks prior to the actual date of the announcements. They reveal that the influence of insider trading enforcement is stronger in countries with more effective judicial systems. The efficacy of the solution is contingent not solely on the quality of the legal framework, but also on the rigour of its enforcement.

The question to ask is whether sanctions and monetary penalties for lawbreakers in the Tadawul lack a credible deterrence effect. Alkhaldi (2016) examines several insider trading cases that occurred in the Tadawul and elucidates that review of the cases by the CRSD did not follow consistent assessment procedures. Further, the author illustrates that the monetary penalties were not sufficiently high to deter insider trading; and that the CRSD as of the end of 2014 had not imposed incarceration for insider trading except in one instance where the sentence was for only three months out of a possible five years.

As per the 2003 CML, Ramady (2010) argues that the prescribed maximum penalty of SAR 100,000 for every instance of insider trading is an excessively mild punitive measure. Alkhaldi (2016) suggests that although Saudi laws adequately define insider trading, these laws and regulations are still partially ambiguous and vary from one case to another in terms of their implementation and the punishments inflicted. The author concludes that several significant systemic shortcomings still exist in the implementation procedures, and they must be addressed when it comes to insider trading and information leakage.

According to Al-habshan (2017), the regulations set out by the CMA are excessively loose and lack the necessary rigour and stringency, thereby affording certain space to insiders and market manipulators and enabling them to achieve their objectives. Empirical study findings support those of theoretical background research. As discussed in Section 1.2, Alzahrani et al. (2013) reveal that informed traders in the Tadawul exhibit a propensity to engage in substantial trading activity and can simply earn abnormal profits, particularly when making block purchases.

In their empirical study, Syed and Bajwa (2018) examine abnormal stock returns to test the market reaction around earnings announcements for firms listed in the Tadawul from 2009 to 2014, and observe significant ARs several days before the official announcement date. These findings are consistent with those of Felimban et al. (2018), which suggests the presence of substantial price changes before dividend decrease announcements and support the authors’ conclusion that markets in the GCC region, including the Tadawul, demonstrate inefficiency because of leakage of information and potential insider trading activities preceding the release of negative news.

In contrast, Alhassan et al. (2019) examines whether earnings announcements on the Tadawul are informative and finds evidence that the market reacts well to earnings announcements because of recent improvements in regulatory performance. These findings may support those of Baamir (2008) who examines the transparency and disclosure provisions in the CML of Saudi Arabia at the time of the study in comparison with predecessors as well as analogous regulations of the London Stock Exchange. The author finds that the Disclosure Rules of the CMA are effective and aligned with global standards, and the enforcement mechanism is reasonably efficient.

However, Baamir (2008) argues that the issue in the Saudi stock market does not stem from inadequate corporate disclosure, but is due to investors’ lack of experience in obtaining and maintaining information. This argument is in line with Alkhaldi (2016) clarifying that many people in Saudi society believe helping others such as offering financial advice is a personal principle and societal duty. Thus, it could be argued that such investors are not actually sure or even recognise that insider trading is wrong, illegal and counterproductive to the efforts of the regulatory agency to promote a fair and efficient stock market environment. Therefore, attracting public attention to increase their awareness about market misbehaviour should not be neglected by the authority.

The CMA’s endeavours are not limited to the enactment of regulations for the CML and MCR. In fact, it has gone beyond the scope of its legislation duties by seeking to increase the public’s knowledge regarding market misbehaviour. According to International Organization of Securities Commissions (IOSC, 2015), boosting deterrents via public messaging is one of the key tasks of the regulatory body to show that 'there are tangible consequences for those engaging or contemplating engagement in misconduct' (p. 34).

The CMA, therefore, issued a series of awareness booklets and instructions to endorse continuous awareness efforts about violations to the rules, particularly those associated with insider trading in the Saudi capital market.[20] The booklet is aimed to enhance public understanding, raise market participants' awareness and support them in avoiding breaches of the law. Alongside the CML and MCR, this handbook provides an overview of insider trading practice including definitions, examples, sanctions, penalties, policies and procedures.

The evidence presented by Alhassan et al. (2019), which indicates that the market reaction to earnings announcements increases over time and that information leakage and insider trading practices decline, leads them to conclude that improvements in market integrity and the informational environment are attributable to the CMA's efforts. In the context of deterrence sanctions and penalties, Table 2.2 shows the number of filed and finalised insider trading violation cases alongside the sanctions imposed by the CMA during the period 2011–20.

Table 2.2

Cases and Financial Penalties of Insider Trading Violation in Tadawul from 2011 to 2020.

Year	Filed	Finalised*	Total amounts of financial penalties & fines imposed in (SAR)
2011	6	4	0
2012	1	2	0
2013	2	-	0
2014	1	2	0
2015	20	25	0
2016	31	28	23,265,510
2017	17	28	2,142,275
2018	18	17	325,222,919
2019	3	3	1,440,380
2020	4	2	0
Total	103	111	352,071,084

Source: The CMA annual reports, 2010–2020. *The finalized cases include cases from previous years. The prevailing exchange rate between the USD and the SAR is roughly 3.75.

[20] https://cma.org.sa/en/Awareness/Publications/booklets/English.pdf

The data were extracted from the CMA’s annual reports for the years 2011–20. Table 2.2 shows 111 instances of insider trading resolved over the course of that decade. These cases resulted in financial penalties exceeding 95 million USD. Later, the CMA disclosed in its 2021 annual report that during the timeframe spanning 1 October 2020 to 30 September 2021, the total amount of fines and monetary sanctions levied against the violators of MCR exceeded 206 million SAR, signifying a surge of 225% in comparison to the corresponding period for the preceding year.

According to the above studies, the essential challenges facing the Tadawul to achieve fairness, accountability and transparency may be attributed to a lack of insufficient credible enforcement of legal regulations, and minimal penalties and sanctions. The prevalence of market misconduct is more likely to hold in markets where the disclosure regime and enforcement mechanisms are poorly implemented. A surprising fact is documented by Bhattacharya et al. (2000) who disclose that share trading does not apparently react to corporate news in the market when weak enforcement is in place. The authors examine corporate news announcements on the Mexican Stock Exchange (Bolsa Mexicana de Valores BMV) from July 1994 to June1997 and provide empirical evidence that unrestricted insider trading causes stock price movements to fail to react to announcements when they become public. However, insider trading commonly occurs in environments where enforcement of regulations is not efficiently implemented.

In sum, despite rules made a long time ago, contemporary legislation has been introduced to prevent market abuse by prohibiting illicit insider trading for all market participants and tightening the obligation on issuers to restrict the disclosure of inside information to proper channels. However, the existence of insider trading and the question of the level of market integrity and fairness are the subject of increasing concerns in the

Tadawul. It is unclear what impact the amended rules have and how well the legislation is enforced. A prosperous law and finance literature effectively demonstrates the essential aspect pertinent to the mentioned argument; that is, the effective enforcement of securities laws. The literature on insider trading laws well documents the importance of enforcing insider trading laws, finding that legislation is pointless unless enforcement mechanisms are enforced strictly; it is not enough to merely introduce the law itself (Bhattacharya & Daouk, 2002, 2009; Carvajal & Elliott, 2009; Kwabi et al., 2018; Ojah et al., 2020).

2.5 Chapter Summary

This chapter presents an overview of the KSA economy and the major restructuring and development that the Tadawul has witnessed since its inception. The chapter highlights the amendments and revisions made by government authorities to the laws and regulatory framework pertaining to illegitimate insider trading practice. The chapter reviews academic research that investigates regulation of Saudi laws relating to insider trading, shedding light on arguments and criticisms aimed at the legal system. Also discussed are cases pertaining to insider trading and enforcement actions imposed by the CMA on those who engaged in illegal insider trading activities, including sanctions and monetary penalties. Chapter 3 expands the review beyond the Saudi context by offering a thorough overview of the world of insider trading practices in a broader context.

Chapter 3: Theoretical Background and an Overview of Insider Trading Practice

3.1 Introduction

The previous chapter provided background about insider trading regulations and enforcement mechanisms in the Saudi setting. It is also useful to provide a better understanding of insider trading practices from a wider perspective. Thus, this chapter presents a comprehensive review of insider trading activities and addresses some issues associated with the most contentious areas of disagreement between the opponents and the proponents of insider trading prohibition. The review is restricted to studies conducted outside the KSA, given that research specifically focusing on the Saudi stock market was discussed in the previous chapter.

This chapter draws on pertinent academic literature examining the impact of insider trading on the fairness of stock markets, trust of investors and market efficiency. A large and growing body of scholarly works investigate insider trading activity from various perspectives. However, this review illuminates only theories and fundamental concepts that fall within the scope of this research. The remainder of the chapter is organised as follows. In Section 3.2, insider trading practice is defined and an overview of the various forms of this practice is presented. Section 3.3 sheds light on the major arguments among scholars regarding debate surrounding the advantages and disadvantages of insider trading. The section reviews empirical and theoretical studies in a range of political, social and economic macro contexts.

3.2 Definitions and Examples of Insider Trading Practice

In general terms, the major characteristics of insider trading practice pertain to material information and its abuse. Insider trading commonly occurs when someone possesses material private information that has the potential to impact the value of shares and exploits their advantage by engaging in trading activities based on the privileged information. When the relevant information is later disclosed to become publicly accessible, it is more likely to have a substantial effect on the security price or trading volume. Therefore, such traders leverage the private information at their disposal for their personal gain, either by realising significant profits in the event of good news or mitigating substantial losses in the event of unfavourable news.

It is crucial to acknowledge that not all types of insider trading are unlawful; certain forms are completely permissible (Shell, 2001). Some corporate insiders may engage in trading of their company stock if they give prior notice about their transactions to the authority of the stock exchange. This study solely examines unlawful types of insider trading. Numerous definitions of illegal insider trading practice are presented in the literature; the majority of these largely align with the concept of abusing inside information. According to the US SEC:

> Illegal insider trading refers generally to buying or selling a security, in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, non-public information about the security. Insider trading violations may also include 'tipping' such information, securities trading by the person 'tipped,' and securities trading by those who misappropriate such information.[21]

Having provided a brief definition of insider trading practice, the discussion now delves into an overview of the world of insider trading practices. Examples of insider trading activities are innumerable. This practice is generally not limited to individuals who hold insider positions in a particular firm. Rather, the range of individuals engaging in such activities may extend to encompass a diverse array of categories in social networks. Studies

[21] https://www.sec.gov/fast-answers/answersinsiderhtm.html

demonstrate that the behaviour of individual traders differs according to their social ties (Ahern, 2017; Jagolinzer et al., 2020; Park et al., 2020) and personal characteristics, such as wealth and job position (Dhar & Zhu, 2006; El-Khatib et al., 2021), gender (Barber & Odean, 2001) and age (Korniotis & Kumar, 2011).

Based on hand-collected data from highly detailed court case documents, Ahern (2017) succeeded in identifying 183 insider trading networks among all insider trading cases filed by the SEC and the DOJ between 2009 and 2013. In terms of the ties and relationships among inside traders, the author shows that strong social connections is one factor because insiders share family relationships, friendships or business relationships. Ahern (2017) examined 461 pairs of tippers and tippees and found that 23% were family members (sibling and parental relationships), 35% were friends and 35% business related.[22]

In their empirical study, Berkman et al. (2014) observe that certain insiders engage in illegal trading activities through their children’s accounts prior to major earning announcements. They arrive at the conclusion that this channel serves as a proxy that yields considerable profits. Besides, insiders tend to share information with people who are closer in age and of the same gender as themselves. Korniotis and Kumar (2011) prove that older investors, especially those with more experience, possess greater knowledge. The average age of insider traders in the sample used by Ahern (2017) was 43 years, the oldest person was 80 and the youngest trader was 19 years old.

Ahern (2017) notes that there is a large gap between two genders balance where 9.8% of the total population being female, 90% of insider traders were men. Thes findings corroborate those reported by Barber and Odean (2001), indicating that women are less likely to participate in insider trading than are men, raising questions about whether women exhibit

[22] The tipper is an individual who has breached their fiduciary duty by knowingly disclosing confidential information. The tippee refers to a person who intentionally utilises such information to engage in a transaction.

greater adherence to regulations and compliance with the law. Alternatively, it can be conjectured women may have more limited access to inside information than do men.

Another shared characteristic of individuals involved in insider networks is occupation. Ahern (2017) shows that the flow of information tends to be from subordinates to bosses, from younger tippers to older tippees, and from children to parents. However, homophily in social networks—such as frequent communication within the same class of people or affiliated industries—is more likely to create an opportunity for insider trading to occur. This statement is in line with several of the most recent studies that show that the most common occupations involved in the sharing of private information is top executive officers, which include chief executive officers (CEOs), chief operating officers and chief financial officers (CFOs). A variety of occupations including directors, investment managers and analysts, as well as a significant number of professionals, such as lawyers, accountants, consultants, engineers and attorneys is also involved.

For example, Cheong et al. (2022) report that hedge fund managers with ties to directors of companies concerned with merger deals raise the call options holdings of target firms prior to public announcements. These findings are based on manually collected information on networks of alumnus reunion cohorts. El-Khatib et al. (2021) demonstrate that CEOs with high network centrality achieve higher ARs, resulting from purchasing shares of their companies than do CEOs with lower network centrality.

Moreover, the findings of Ben-David et al. (2019) indicate that purchases made by insiders who are not executives significantly parallel those purchases made by executives insiders. In his investigation of informed traders in nine types of occupation, Ahern (2017) finds that the top executive occupation ranked first with 107 individuals. The author notes that 9.5–15% of all insider trades were made by top executives. The findings presented so far suggest that occupational ties may be regarded as a pivotal element in the dissemination of private information.

Other research shows that the prevalence of insider trading can extend beyond the boundaries of firms. For example, in their analysis of the trading activities of corporate insiders in prominent financial institutions throughout the global financial crisis period spanning 2007–09, Jagolinzer et al. (2020) provide compelling evidence of a correlation between political connections and informed trading by officers and directors, particularly among corporate insiders who had recent direct connections during the period of disbursement of the Troubled Asset Relief Program (TARP) fund. The authors conclude that political communication can serve as a means for corporate insiders to engage in opportunistic conduct of insider trading. In a wider context, Park et al. (2020) observe that domestic institutional investors engage in a greater degree of information-based trading than do foreign institutional traders.

In summary, this review has shown that social networks play a critical role as a means of private information diffusion. One may ask if such cases emerge from investors' lack of awareness in maintaining and abusing private information. Further, it could be predicted that this practice is motivated by an individual's belief that providing financial advice is a community duty and a personal principle without recognizing that they are implicating in illegal practice. Finally, as the common view is that insider trading is illegal and unethical, such patterns of behaviour may have less respect for the rule of law, or accountability apathy. Alternatively, insider trading might result from ambiguous rules or weak enforcement of securities regulations. This section has provided a brief summary of the literature relating to definitions and examples of insider trading practice. The section that follows reviews controversies in the literature about insider trading from several aspects.

3.3 Vigorous Debate Between Proponents and Opponents of Insider Trading Prohibition

Insider trading has offered fertile ground for discussion in terms of both unethical considerations and an economic perspective. Debate around insider trading in stock markets has been intense over a number of decades in several areas such as law, economics, culture and finance. Several prominent scholars in securities law and financial markets have extensively debated whether insider trading is harmful or good for securities markets and market participants. Given the significance of integrity in the stock market and its impact on investor confidence, market misconduct such as insider trading has attracted considerable attention from researchers over time.

It is documented that for over three centuries insider trading was legally permitted until the introduction of the *Securities Act of 1933* and the *Securities and Exchange Act (1934)* in the US (Dalko & Wang, 2016). These laws were adopted with the objective of regulating market misconduct deemed to have played a role in the stock market crash of 1929 in the US.[23] Prior to enactment of these laws, insider trading practice was not considered illegal. Thus, the evolution of laws against insider trading has been based on a great deal of debate among academics, experts and regulators.

A vast literature is devoted to the serious harm that insider trading does to the capital market's reputation, integrity and transparency, such that it requires strict regulation. Another school of thought argues in favour of insider trading, stating that it fosters market efficiency and is an efficient method to compensate corporate managers. Some academics take a middle position, arguing that insider trading practice has both positive and negative effects. The question of whether insider trading should be legalised or subject to strict oversight remains a

[23] SEC Speech: Insider Trading - U.S. Perspective (T. Newkirk, M. Robertson)

topic of debate. This section sifts through and scrutinises controversies involving the various positions taken in the literature about the benefits and harms of insider trading.

To address the debate between the two main schools of thought in line with theories, it would be beneficial and practical to use an example of insider trading to critically articulate and analyse the arguments of the different points of views. The distinguished work of Bhattacharya (2014) is probably a good place to start as it addresses controversies about insider trading practice and presents an explicit example of the occurrence of this practice and its consequences.

In his hypothetical case, Bhattacharya (2014) supposes that he is a manager of firm X that produces luxury earphones. His head researcher informs him that their new preliminary model is 75% accurate at identifying a user’s mood and playing music suited to that state of mind. Bhattacharya discusses this confidential information about the product with Newton, the president of company’s advertising agency. Newton subsequently reveals this material non-public information to his friends who run an unrelated music business. Bhattacharya, Newton and Newton’s friends buy stocks in Bhattacharya’s company on 13 August 2013, and the stock price sharply increases by 50% and runs up from 10 USD to 15 USD on that day. A few shareholders—outsiders—sell their shares at 15 USD. A couple of weeks later, the firm publicly discloses the information about the product and the share price consequently increases to 20 USD. After several months, Bhattacharya, Newton and Newton’s friends are convicted by the SEC for insider trading in a civil case.

Using this example, the chapter now endeavours to analyse the potential advantages and disadvantages of insider trading from several perspectives.

3.3.1 Insider Trading as an Efficient Compensation Mechanism

Although most scholars maintain that insider trading practice should be prohibited because of its significant harmful effects, the main supporters of deregulating insider trading, such as Henry Manne (1966) and Carlton and Fischel (1983), argue that there are considerable advantages to legalising insider trading practice. An early proponent of insider trading, Manne (1966) identifies three main points that justify making insider trading legal. First, the act of engaging in insider trading serves as an effective means for compensating managers. The second point is that long-term investors are not significantly harmed by insider trading. Third, and of greater significance, permitting insider trading will result in enhancement of price informativeness through their trading activities, and thus improve market efficiency.

Regarding the first point, Manne (1966) argues that an economic service can be obtained through the practice of insider trading by compensating firm insiders for their entrepreneurial efforts. The author considers that the opportunity to profit from insider trading is an alternative compensation mechanism for corporate managers for their performance and innovations. Carlton and Fischel (1983) support Manne's claim, arguing that insider trading is a less expensive and intensive device, and an efficient mechanism for compensation of corporate managers for the information they produce when they operate a firm. These arguments are grounded in an economic perspective and suggest that allowing the conduct of this practice by insiders is reasonable given the valuable information that insiders generate and is an efficient way to pay a lower base salary.

Even though removing restrictions from managerial trading and rewarding managers for their efforts will in itself increase productivity, shareholders may have further incentives to allow insider trading. For instance, Noe (1997) shows theoretically that the opportunity for insider trading provides only partial reward for efforts compared with effort-assuring compensation contracts, which may demand higher payouts. Thus, insider trading can be used as a low-cost incentive tool in the place of more expensive compensation strategies. In line with this view, Roulstone (2003) indicates that companies that impose limits on insider trading tend to offer a higher compensation premium than do firms that do not impose restrictions.

Other critics of regulating insider trading contend that insider trading enhances the managerial labour market by assisting companies in distinguishing between managers of superior and inferior quality (Carlton & Fischel, 1983; Easterbrook, 1985). This is because exceptional managers would be inclined to accept a compensation structure that incorporates insider trading, as they would have the ability to generate valuable information. Conversely, underperforming managers would not possess this capability.

Manne's major argument, along with later arguments in favour of insider trading practice has faced a great deal of criticism. One of the limitations with the argument might be that it does not precisely explain the extent to which insiders can benefit from such practice. Specifically, the argument refers to compensation in general terms, but does not quantify the amount (Schotland, 1967). Schotland, one of Manne's early critics, argues that a salary is suitable for purchasing a specific service in the labour market; however, bonuses and stock options are unsuitable for compensation purposes.

Another criticism is that this form of compensation is not necessarily restricted to individuals who are entrepreneurs in the company. Cox (1986) claims that ensuring that the producers of valuable information—namely innovators—are those being compensated is a challenging task in practical terms. Drawing on Bhattacharya's luxury earphone example, this view is unquestionably consistent with the stance involving Newton's friends. Newton is the head of an advertising agency who divulges confidential information to his friends; therefore, though they are not affiliated with the firm they personally profit by trading on the basis of this inside information. Additionally, McGee (2010) comments that this form of compensation is not inherently linked to the level of performance. The author suggests that in the event that a firm's stock is expected to decline in value because of managerial insufficiency, insiders responsible for the decline can benefit by selling their shares prior to the information being made available to the public because of their privileged knowledge.

Finally, the argument that permitting insiders to trade on inside information is an effective compensation tool has been criticised from an economic perspective. Ausubel (1990) examines the issue from an economic viewpoint and finds that an equilibrium that maximises one party's welfare without a corresponding reduction in the welfare of another party is unattainable. In the context of insider trading, this implies that the benefits that insiders derive from engaging in insider trading would be counteracted by a reduction in investment resulting from reduced participation of outsider investors who are aware of their disadvantage (Bhattacharya, 2014; King & Roell, 1988). Subsequent sections delve into contentious aspects surrounding the diverse stances taken in scholarly works concerning the pros and cons of insider trading practice.

3.3.2 Agency Theory and Conflict of Interest

In addition to the issues discussed above, a serious weakness with the compensation argument might be that the practice exacerbates major conflicts of interest. The presence of a conflict of interest between shareholders and managers gives rise to the agency cost problem. The theoretical framework centred on agency theory in the context of insider trading postulates there is an impact of insider trading on the corporate agency issue concerned with conflict of interest between managers and owners.

As per the tenets of agency theory established by its pioneers, in situations where both owners and control entities prioritise utility maximisation, there is a significant likelihood that the agent may not consistently act in the best interests of the principal (Jensen & Meckling, 1976). The authors claim that the principal is able to restrict deviations from their interests by providing suitable incentives to the agent and by incurring expenses for monitoring intended to curtail any deviant actions of the agent.

Although Carlton and Fischel (1983) argue that the existence of a certain level of conflict of interest is inevitable if a manager does not own the whole company, Fama (1980) states that when the wage revision process carries the same weight as complete ex post settling up, any managerial incentive issues typically associated with the separation of security ownership and firm control are effectively resolved. Skaife et al. (2013) empirically investigate the correlation between ineffective internal control mechanisms for financial reporting and the profitability of insider trading. Their study focuses on insider trading transactions by CEOs and CFOs among 4,505 firms from 2004 to 2008. Their interesting findings indicate that the level of profitability associated with insider selling by CEOs and CFOs is positively correlated with the probability of their departure from their respective firms. In the same vein, Armstrong et al. (2021) investigate whether CEOs acquire stocks to prevent being dismissed. The authors present empirical evidence that some CEOs can derive certain indirect advantages from long-term employment that significantly impact the overall profitability of their transactions.

Further criticism that could be made of this line of reasoning is that allowing the practice of insider trading may lead insiders to use information that accords with their personal interests. For instance, insiders may choose a time that suits their interests to take advantage of information either by delaying or accelerating announcement dates (Cheng & Lo, 2006; Feng, 2023; Haft, 1982). Empirical studies show that corporate insiders strategically time their trades in their respective firms around the disclosure date of annual earnings announcements (Katselas, 2019; Penman, 1982), M&As and takeover events (Davis et al., 2020; Keown & Pinkerton, 1981; Suk & Wang, 2021); in this way they achieve significant ARs. The possession of privileged information by insiders could harm the interests of minority shareholders (Li et al., 2020).

Other studies show that in addition to exploiting major economic events, insiders time their trades around voluntary disclosures to maximise their wealth (Feng, 2023; Noe, 1999). Cheng and Lo (2006) provide evidence that insiders utilise opportunities for voluntary disclosure to gain personal profits, but do so in a limited manner, primarily when legal action is not pending. The authors observe that insiders increase the number of bad news forecasts to lower the purchase price for the shares they intend to acquire. They note that this case is more pronounced in trades instigated by CEOs than for those initiated by other executives. Ahern (2017) examines the wealth of insider traders based on the value of their homes and finds that they are the wealthiest people. In September 2014, the average insider's home was estimated at 1.1 million USD.

More recent empirical research documents that insider trading profitability is much greater when insiders are more likely to act in their own self-interest. Armstrong et al. (2021) show that the average ARs earned by some CEOs from their purchases experience a significant increase, from 3% to 58%. Recently, Feng (2023) investigated the underlying incentives of listed companies to make public commitments and the extent to which they adhere to them. Drawing from a dataset of stake-raising plans made by major shareholders and executives of Chinese A-share listed firms between July 2015 and June 2019, Feng's findings indicate that the self-interest motivation, as measured by the promiser's share pledge ratio, is a significant driving force behind the fulfilment of these commitments.

This review has thus far discussed arguments that rely heavily on the assumption that allowing insider trading is an adequate compensation mechanism that ought to be utilised to remunerate corporate managers. The exacerbation of the conflict of interest and consequent escalation of the agency problem resulting from insider trading practices has also been explicated. The conclusion from debates around this argument is presented in Section 3.3.5. The chapter now shifts focus towards another area of contention.

3.3.3 The Fairness and Integrity Argument

Although numerous arguments have been put made against insider trading in the belief that the practice damages market fairness, there is room for disagreement on this point. In the context of upholding integrity and fairness in the capital market, a pertinent question is whether the act of selective disclosure of inside information to a particular group of investors would destroy the integrity of markets and undermine the confidence of investors. However, the challenge with the argument pertaining to fairness lies in the difficulty of precisely defining the concept of fairness. This is because the perception of fairness can differ between individuals; what one person considers fair may be perceived as unfair by another. Critics have pointed out that the fairness argument lacks precision (Easterbrook, 1981; Strudler & Orts, 1999).

Nonetheless, McGee (2010) claims that one accepted perspective regarding the fairness argument is that a transaction can be deemed fair if it is a product of voluntary exchange, but considered unfair if the exchange is forced. McGee investigates fairness in terms of the process rather than the destination. The author analyses insider trading from various perspectives and posits that in most cases, insider trading is simply the legitimate exercise of property rights. From a rights-based perspective, it cannot be definitively asserted that insider trading is inherently unethical; rather, this is contingent on the determination of whether someone’s rights are being violated.

Insiders use of private information has been regarded as a type of property right. This perspective takes the position that the possession of confidential information is a form of property right, and preventing individuals from engaging in transactions involving said property constitutes a violation of this right. Mc Gee (2010) presents an alternative viewpoint regarding the favourable nature of permitting insider trading, suggesting that there is no abuse inherent in permitting workers who dedicate dozens of hours per week to produce valuable information as a component of their occupation deriving gain from inside information; however, it is unjust to compel such workers to reveal information to those who have done nothing to deserve it.

However, to say that insider trading is merely a practice of property rights is to ask what enactment formalises the right to benefit from private information. It appears that this position does not clearly indicate who entirely owns the right to take advantage of non-public information. Moreover, it could be said that the information belongs to the firm because the effects of this information may influence its shares. That being the case, shareholders may also have a right to exercise rights over the information that can impact their property. It could be asked whether the information is produced by insiders alone or is a result of cooperative work involving other shareholders.

Further, to say that insider trading is a practice of property rights is to claim it is another source of income and wealth. Through this lens, it could be questioned why such a property right is only exercised by insiders. Others may argue that this issue can be viewed from a different perspective, which is that insider trading may be considered an additional income source for the firm and should be maintained and benefited from by all parties. However, Durnev and Nain (2007) conducted a study on 2,189 firms across 21 countries, and their empirical findings show that managers who work in firms that impose restrictions on insider trading tend to engage in covert expropriation of their firm’s resources.

Under these circumstances, it could be argued that such a scenario may transform the stock market into a platform for trading information with the aim of generating profits, even if such information ultimately proves to be mere rumours. Studies show that insiders may manipulate the market by disseminating misleading information to purchase at a lower cost or sell at a higher one (Levmore, 1988). By the same token, Cheng and Lo (2006) find that managers issue a higher number of negative news forecasts to lower stock prices prior to purchasing their shares. Empirical evidence provided by Skaife et al. (2013) supports the notion that increasing profitability associated with insider selling by top management is attributed to a lack of integrity.

Going back to the Manne argument, he presents his second viewpoint by stating that insider trading practice rarely causes harm to the long-term investor. This argument may be examined in relation to Bhattacharya's example, particularly via the case of the shareholders—short-term investors—who sell their shares prior to the announcement date at a price of 15 USD and thus sustain a loss of 5 USD per share. On the day when the information is revealed, prices increase from 15 USD to 20 USD per share; therefore, other shareholders—long-term investors—who decide to keep their shares enjoy the profits of a significant increase in share value. Regarding harmful impacts, the fairness argument is considered one of the main points of contention; many believe that insider trading is unfair and damages public trust in capital markets.

It is clear how insider traders benefit from private information and disadvantage other investors. Specifically, the Bhattacharya case illustrates a monopoly and abuse of private information where insiders exploit their superior access to material information and dispense this information to certain shareholders who are able to profit at the expense of outsiders. Given that the material private information in this example is misappropriated, the case relates to misappropriation theory, which is based on the premise that 'self-serving use of principal's information to purchase or sell securities, in breach of a duty of loyalty and confidentiality, defrauds the principal of the exclusive use of that information' (McCord et al., 2011, p. 145).

Arguably, if individuals with access to privileged information are granted unrestricted permission to engage in insider trading activities, why is such access and permission not extended to other shareholders? It could be argued that limiting access to inside information, making it freely available to insiders is unjust, not only because a segment of shareholders is denied their right to know the information, but because they cannot benefit equally from the valuable knowledge in the presence of permission for one party to monopolise it at the cost of others (Salbu 1989). The practice of insider trading is detrimental to the fundamental principle of equitable information access for all participants in the securities market (Deng et al., 2019). Feng (2023) claims that major shareholders may initially pledge to augment their holdings to mitigate any further reductions in the stock price. Subsequently, they may gradually fulfil their obligations to stabilise the stock price in a prompt manner with the aim of safeguarding their own interests.

In the Bhattacharya example, a case could be made on both ethical and economic grounds to prohibit insider trading. First, if insiders are permitted to benefit from inside information and distribute it to their friends who subsequently trade on the information, market fairness and integrity would be damaged (Bhattacharya, 2014). From an economic perspective, if the market is perceived as manipulated exclusively in favour of insiders, outsiders will withdraw from the market to avoid engaging in transactions with insiders who can only benefit from transactions (Bhattacharya & Dauok, 2009). Such a case is critical as it has the potential to dissuade investor involvement in the market because of the lack of confidence and fairness, which may lead to less liquidity and a possible collapse of the market.

Although the above argument employs valid reasoning, it is likely more controversial when counterbalanced with the considerable merits of insider trading, which are an improvement in market efficiency. In his reply to Manne's thesis, Schotland (1967) argues that ethical considerations—specifically those pertaining to justice, fairness and integrity—may take precedence over financial justifications when evaluating the benefits of insider trading. The efficiency aspects of insider trading practice is discussed in the following section.

3.3.4 Market Efficiency Theory

In addition to the above arguments surrounding the pros and cons of insider trading dealing, scholars have extensively debated the unique characteristic that insider trading activity may produce, which concerns its role in enhancing market efficiency. The last and most important point made by Manne (1966), one of the principal advocates for insider trading, is that insider trading practice improves market efficiency. Carlton and Fischel (1983) support Manne's assertion, stating that insider trading is beneficial to market efficiency because it improves the formation of stock prices.

The simple explanation for the above statements is that trading on inside information serves as a channel that more efficiently imparts information to the marketplace than would otherwise be the case. To illustrate, insiders possess privileged knowledge. Consequently, when they purchase shares, the price increases and when they sell, the price decreases. Thus, information is conveyed into prices. However, if their trades are confined, the information cannot be incorporated into prices, which may result in weak market efficiency.

When considering Manne's argument in light of the example of Bhattacharya mentioned in Section 3.3, it appears to bear a great degree of validity. This is particularly true in the scenario where insiders trade on the day prior to the disclosure date, and the share prices sharply increase from 10 USD to 15 USD. These movements are driven by insider trading activities already reflected in the stock price. Such unusual price movements send a proactive signal that there is a forthcoming event that can influence the share value. Prior to delving into the extensive body of research examining the impact of insider trading on market efficiency, the primary focus here is to align the consistency of the market efficiency concept with the fundamental theoretical framework of financial markets. It is obvious that the mentioned case is associated with the EMH; in particular, the semi-strong form.

The EMH is a fundamental principle in financial economics that has garnered substantial empirical support. In his seminal work, Fama (1970) presents the theory of EMH, which pertains to the extent to which prices, at any given time, fully reflect all available information. The EMH is classified into three forms: weak, semi-strong and strong form tests of market efficiency. Weak form tests rely solely on historical price information. A market that transmits historical market data and past prices into share prices, yet fails to accurately forecast future prices, is classified as a weak form efficiency market (Asiri & Alzeera, 2013).

Semi-strong form tests examine whether prices adjust efficiently to publicly available information. A market attains the status of a semi-strong form when share prices digest the entirety of publicly accessible information. In this case, the existence of ARs after the release of insider trading information should not be observed (Glosten & Milgrom, 1985; Seyhun, 1986). The method of market cleanliness, which is employed in the present study, is supported by the EMH. The substantial presence of ARs once an announcement is published pertain to the examination of a SA as previously defined. Further, the investigation of APPMs aligns with the strong form of the EMH, as we shall see in the following paragraph.

Regarding the third form of the EMH, a market can be deemed to possess strong form efficiency if the share price comprehensively reflects all publicly available and private information. Strong form tests focus on determining whether specific investors or groups possess exclusive access to any information that is pertinent to the price formation (Fama 1970). This hypothesis has undergone testing and is confirmed in the literature through the utilisation of registered insider trading data gathered from the SEC.

One of the early investigations was that conducted by Jaffe (1974) who discovered that a trading strategy that relies heavily on registered insider trading can outperform the market, leading to the conclusion that registered insiders possess special information and can achieve superior returns. Jaffe's work was extended by Finnerty (1976) who examined the full sample of registered insider transactions for the years 1969–72. His findings support those of Jaffe, indicating that registered insiders can outperform the market when engaging in both buying and selling activities. The theoretical and empirical literature provides evidence that the practice of insider trading has an impact on the informational efficiency and discovery of prices prior to the release of news (Baruch et al., 2017; Bolandnazar et al., 2020; Collin-Dufresne et al., 2021; Glosten & Milgrom, 1985; Kyle, 1985).

Regarding market efficiency, Meulbroek's (1992) study reveals interesting results pertaining to the trading activities of individuals accused of engaging in illegal insider trading practice. The author discovers that 50% of observed price increases prior to takeover announcements took place on days when illegal insider trading occurred. The author concludes that the market can detect potential instances of illegal insider trading where such trades impound information into share prices prior to public disclosure, thereby promoting market efficiency. Meulbroek's results for rapid price adjustments and efficient price discovery lend credence to Manne's, and Carlton and Fischel's contention that insider trading fosters market efficiency.

Likewise, Keown and Pinkerton (1981) investigated the price reaction of trading to private information before scheduled takeover events of 194 companies acquired during 1975–78. Their analysis is based on the daily stock price performance. The authors provide empirical evidence that ARs achieved by investors in acquired firms demonstrate that the response of the market to anticipated mergers starts 12 days prior to the initial public disclosure of the proposed merger.

Similarly, Syhun's (1986) analyses around 60,000 transactions involving insider sales and purchases spanning from 1975 to 1978. Syhun presents evidence that insiders possess the ability to forecast future abnormal changes in stock prices, differentiate the varying degrees of worth of their information and make more trades to take advantage of valuable information. Later theoretical models such as those by Leland (1992), Shin (1996) and Noe (1997) imply that insider trading increases the responsiveness of stock prices to changes in the market. Additionally, recent empirical studies support the hypothesis that insider trading can forecast news and forthcoming returns (Barucha et al., 2017; Collin-Dufresne & Fos, 2015; Jagolinzer et al., 2020; Suk & Wang, 2021).

For example, the study of Jagolinzer et al. (2020; discussed previously in Section 3.2) is concerned with the role of political connections in facilitating opportunistic behaviour by corporate insiders. The authors analyse the trades made by insiders over 30 days before TARP infusion and provide evidence that abnormal trading conducted by insiders with political connections occurs over the 30 days ahead of TARP infusion. The authors further note that these trades anticipate both the market's response to the infusion and discrepancies in infusion amounts.

Further, Kacperczyk and Pagnotta (2019) examine the trading behaviour of inside traders, using a dataset comprised of over 5,000 trades based on private information pertaining to the underlying fundamentals of firms. They find that stock returns have a significant reaction to trades made by insiders, with the average direction of private information being reflected in the changes observed. Akey et al. (2022) investigate the ability of market makers to identify and react to sudden surges in informed trading. Their findings reveal a significant increase in equity volume, equity turnover and option volume in stocks accessible to traders informed about upcoming earnings news.

In a similar fashion, Suk and Wang (2021) use a sample of 5,313 individual insider transactions from 1986 to 2016 to investigate the feasibility of utilising a target firm's net insider buying as an indicator of the potential acquisition for a firm seeking a takeover target.

Their findings are consistent with previous studies such as Keown and Pinkerton (1981), in that that there is information leakage about upcoming events ahead of public announcements. They conclude that target insider net purchases ahead of M&A announcements are informative and enhance the efficiency of the M&A market.

Although insider trading enhances market efficiency, other studies discover that insiders can prudently manage their trade to avoid causing unusual price movements and safeguard themselves against prosecution (Ahern, 2020; Collin-Dufresne & Fos, 2015). Under this circumstance, it could be argued that trading on inside information is a tactic that avoids reflecting insider activities into price and thus may not prompt market efficiency. In addition, a large and growing body of literature shows that insider trading may aggravate other issues such as adverse selection risk, increase trading costs, increase information asymmetry and affect market liquidity.

For further elaboration through a different lens, let us reconsider the Bhattacharya example mentioned in Section 3.3. Once insiders conduct trade based on inside information, the price jumps by 5 USD even though the announcement has not been publicly made. Behaviour changes in the stock price send a signal to outsiders who are not privy to the inside information. Alldredge (2015) hypothesises that attentive insider trading informed by public information indicates that corporate insiders look for public information that is associated with their firms and profit by trading when outside investors are relatively inattentive.

The situation can also be apparent to attentive outsiders who become aware of the potential for engaging in transactions with insider traders. As a result, outsiders may purchase at a lower price and later sell at a premium to offset the negative effects of this adverse selection (Bhattacharya, 2014). Bagehot (1971) believes that this is the informational source for bid–ask spread. However, the theoretical model of Fishman and Hagerty (1992) demonstrates that this spread discourages other traders from engaging in such trading. In the same fashion, Glosten and Milgrom (1985) theorise that a specialist faces an adverse selection risk when outsiders agree to trade at the specialist's ask or bid price; outsiders may trade because they recognise something that the specialist does not. Such a spread, therefore, may prevent other traders from obtaining information or making a trade.

A considerable body of market microstructure literature pioneered by Kyle (1985) and Glosten and Milgrom (1985) and extended by Collin-Dufresne and Fos (2015) and Ahern (2020), among others, searche for trades with liquidity and asymmetric information—as measured by different metrics—and finds an increase in information asymmetry among market participants. Kyle (1985) employs a dynamic model of insider trading to investigate the information content, liquidity and value of inside information to insiders. The author constructed his model using three types of trader: (1) the single insider who has private information about liquidation value; (2) uninformed noise traders who randomly trade; and (3) market makers who set prices efficiently. Kyle observes that noise trading creates a camouflage that hides insider trading from market makers. This enables insiders to make a profit at the expense of noise traders, whereas the market maker cannot identify the trading of either type.

Kyle also notes that, in a continuous-time setting, the informed trader continually trades in an optimal way where their private information is gradually incorporated into prices. Bolandnazar et al. (2020) explore how the reduction in trading intensity and the price assimilation of information are associated with an anticipated delay in public disclosure, but noise trading and the relative information advantage exhibit comparable effects as in microstructure theory, which assumes that speculators use market orders to take advantage of their private information.

According to Bagehot (1971), market makers incur losses when engaging with investors who possess privileged information. This is because of the significant spread between bid and ask prices offered by market makers, which discourages investors from trading on information that may result in a minimal shift in the equilibrium price. Under such conditions, these investors may refrain from engaging in transactions with the market maker, thereby precluding any potential earnings for the latter unless they misestimate their confidential information.

In their classic model, Glosten and Milgrom (1985) examine how the spread arises from adverse selection, investigate the factors that decisively influence the nature of the spread volume and examine the informational characteristics of transaction prices. They note that information-based spread may cause realisable returns to be overestimated relative to returns that are available to a trader without inside information. With respect to informational content, the researchers report that prices reflect slightly more information than was available to the specialist at the time that bid and ask prices were placed, constituting a semi-strong form of efficiency. Ahern (2020) highlights a different channel of spread that has an effect on prices, indicating that certain companies may have a greater dependence on outside contractors who have a higher probability of spreading inside information.

In terms of price discovery, it is important to understand how insider traders decide on their trading strategies. Studies demonstrate the ability of insiders to camouflage and disguise their activities by timing their trades, conducting stock purchases or selling gradually to avoid influencing stock prices. In their examination of a sample of trade transactions reported in Schedule 13D filings by activist investors, Collin-Dufresne and Fos (2015) disclose that activist investors employ extensive use of limit orders when public disclosure is not imminent and time their trades when liquidity is high.[24] The authors present considerable evidence that insiders tend to engage in trading activities during periods of abnormally high liquidity and low measured adverse selection. They further assert that conventional measures of adverse

[24] The evidence pertaining to the utilisation of limit orders in Collin-Dufresne and Fos's (2015) study is indirect as Schedule 13D filings do not mandate investors to reveal the type of orders placed.

selection lack robustness in detecting the existence of informed trading by strategic traders who possess the ability to make attentive decisions regarding the timing and manner of their trades.

Further, Baruch et al. (2017) demonstrate that tactics employed by informed traders have an impact on the price discovery preceding corporate events. The authors observe that in situations where short selling is expensive and negative news has a limited impact, informed traders employ limit orders. Alternatively, when news is seen to have positive effects, particularly when negative news is significant and short selling is less costly, informed agents anticipate competition and opt to use market orders.

In their study of a single informed trader with long-lived information and stochastic noise trading, Collin-Dufresne and Fos (2016) observe that an insider with long-lived information strategically trades when the trading volume of noise trading is high, demonstrating a negative relationship between illiquidity and insider trading. In such a case, Ahern (2020) predicts that when there are restricted trading opportunities, insider traders experience a lack of chance in terms of timing their trades in a strategic manner to align their trades with noise trades.

The findings of Collin-Dufresne and Fos (2016) are supported by Bolandnazar et al. (2020) who discover that trading using limit orders is preferred to that with market orders when the expected delay of disclosure is longer, market-wide trading volume is large and volatility is low. Bolandnazar et al. (2020) study trade patterns when the SEC inadvertently distributed securities disclosures to a small group of private investors a few seconds before the information was widely available to the financial markets as a whole.[25] Their analysis of this unique setting shows that informed investors trade more aggressively when the expected

[25] https://www.wsj.com/articles/fast-traders-are-getting-data-from-sec-seconds-early-1414539997

release of the news is closer, the value-price divergence is larger, and the filing involves high information content.

The overview so far has shown the benefit of insider trading for market efficiency as exemplified in the efficient absorption of information into stock prices. While the empirical and theoretical studies discussed above document that insider trading transactions are informative of security prices and foster market efficiency, a plethora of other studies document other problems attributable to insider trading activity. Given that the pros of illegal insider trading practice are counterbalanced by its considerable cons, this may explain why many countries have enacted stringent rules that prohibit the practice. This can be attributed to the fact that its perceived benefits are outweighed by its significant drawbacks.

3.4 Chapter Summary

This chapter provides an extensive review of the literature pertaining to the practice of insider trading in terms of definitions, examples and relevant theories, as well as the methods employed by insider traders to obtain the benefits from the practice. The chapter describes numerous forms of insider trading and addresses debate among researchers pondering if the potential benefits from insider trading practice can justify its potential drawbacks. The chapter discusses numerous controversies surrounding insider trading because of its effects on investor confidence and market efficiency and integrity. The next chapter demonstrates how a vast body of literature shows that securities laws matter as they are a critical factor in promoting the development of financial economics and maintaining market discipline and investor confidence.

Chapter 4: Literature Review

4.1 Introduction

This chapter more comprehensively reviews pertinent literature regarding laws governing insider trading, including theoretical and empirical studies, to develop the study hypotheses and address the RQs. The chapter also reviews the significance of enforcement mechanisms in tackling insider trading practice and identifies the respective research gaps. An extensive review of empirical studies that present methodologies suitable for estimating and assessing the extent of insider trading is presented.

The remainder of this chapter is organised as follows. Section 4.2 sheds light on the securities laws of capital markets and their role in improving the economic growth in a country. This section is divided into three sections as follows. Section 4.2.1 provides a review on insider trading regulations and Section 4.2.2 narrows the discussion to enforcement mechanisms and the significance of restricted enforcement of laws against insider trading practice. Some of the measures used in the literature to assess the enforcement of insider trading rules are reviewed in Section 4.2.3. Section 4.3 aims to provide a methodological review on approaches that enable estimation and detection of potential insider trading activities. In the area of capital market research, event study methods are used to examine the impact of insider trading on both stock prices and trading volume performance. Thus, a review of both return- and volume-based event studies is presented in Section 4.3. The section also discusses the design and statistical properties of event study methods employed in the literature to develop research hypotheses.

4.2 Securities Laws and Capital Markets

The level of development of a country's financial markets is often singled out as an indicator of the state of its economy. Numerous studies provide evidence that securities laws matter in a country as they are a crucial factor in the development of its financial markets

(King & Levine, 1993; La Porta et al., 2002; Porta et al., 1998). A growing body of theoretical and empirical literature including wide cross-country comparisons, studies on single countries and studies at the level of companies and industries demonstrates a strong positive relationship between the performance of the financial system and long-run economic growth (La Porta et al., 2006; Levine, 1998).

Improved securities laws indeed have substantial effects in developing capital markets which in turn contribute to the improvements in the economic growth level of a country. This statement is largely in line with the early work of King and Levine (1993) and Porta et al. (1998) who document that regulation of securities laws is associated with the development of equity markets and contributes to economic growth. Further, the financial development level is clearly an essential predictor of economic growth and may be quite a major indicator rather than a causal factor (Levine & Zervos, 1998). Rajan and Zingales (1998) support the results reported by King and Levine (1993) and Levine and Zervos (1998) indicating that the economies of countries with advanced developed legal systems and financial sectors heavily financed from external resources tend to grow faster than others.

However, there is debate around the direction of causal effects; that is, whether financial development drives economic growth or vice versa. Some scholars support the view that development of financial systems is driven by economic growth. Goldsmith (1969) is a pioneer of seminal efforts to interpret the connection between financial system functions and economic growth. Goldsmith traces the linkage between financial development and the rapidity of economic growth using data from 35 countries during 1860–1963. The author uses the value of financial intermediary assets divided by Gross National Product to test the hypothesis that in developing countries, growth leads finance because of the increasing demand for financial services. The researcher finds an approximate correlation between economic and financial development when examining periods spanning multiple decades indicating that the limited number of countries, for which the data is available, of accelerated economic expansion, although with some exceptions, have generally coincided with a higher average rate of financial development.

However, Levine and Zervos (1998) argue that there are several shortcomings in the work of Goldsmith, among them being the limited investigation of only 35 countries, lack of systematic control of other variables impacting economic growth and lack of identification of the direction of causality between the size of financial structures and economic growth. Therefore, Levine and Zervos (1998) investigate the relationship between the legal framework and banking development, tracing the correlation over the long-run rates of per capita Gross Domestic Product growth, capital stock growth and productivity growth. They demonstrate that countries with legal systems that stringently enforce laws have better-developed banks than countries in which legislation enforcement is lean.

Other research on the relationship between financial development and economic growth, like Goldsmith (1969) and Levine and Zervos (1998), use cross-country analysis to investigate the relationship. Although their findings indicate that financial systems help to predict growth, Hassan et al. (2011) argue that studies that use cross-country analysis do not properly handle the issue of causality, nor do they take advantage of the time series characteristics of data. Therefore, Hassan et al. (2011) investigate the dynamic relationship between economic growth and financial development across geographic regions and income groups using time series analysis. Their sample includes 168 countries over the period 1980–2007. In agreement with studies mentioned earlier (e.g., King & Levine, 1993; Levine & Zervos, 1998; Porta et al., 1998), Hassan et al. (2011) find a strong long-run link between financial development and economic growth. Their findings are also consistent with the work of La Porta et al. (2006), who demonstrate that regulation of securities matters is associated with equity market development.

Along similar lines, La Porta et al. (1997) find that countries with weak investor protections laws de facto have narrower and smaller capital equity markets, and that securities laws are crucial for a nation's financial development and governmental prosperity. According to Bhattacharya and Daouk (2009), if companies cannot raise money from outside investors, they will not be able to make profitable investments, leading to a decrease in growth, creation of wealth in society and employment. Taken together, the evidence provided by the aforementioned studies articulates the importance of the legal system in fostering economic growth and development.

Despite the abundance of literature underscoring the importance of regulating securities markets and establishing a structured environment characterised by fairness and integrity, there is a contrasting viewpoint advocating that markets should be left to lead. This view is associated with the hypothesis of Coase (1960) and Stigler (1964) that suggests that optimal government policy is to leave security markets alone unregulated. Moreover, Romano (2001) states that regulation to date has not increased social welfare because it demands disclosure and is unlinked to interfirm externalities that would not be implemented by the market's cost–benefit calculations.[26]

In sharp contrast to Coase (1960) and Stigler (1964), many scholars such as Porta et al. (1998) and La Porta et al. (1999, 2006) have researched the determinants of law and financial development, clearly corroborating that capital markets can only work when good securities laws exist. Grossman and Hart (1980) indicate that the idea behind the hypothesis of Coase (1960) and Stigler (1964) is simply that firms have an incentive to disclose information to raise money and achieve higher prices because investors will assume the worst if firms fail to disclose. La Porta et al. (2006) suggest that investors can make decisions based

[26] However, Romano supports the view of opening international securities regulation at a great degree of regulatory competition to alleviate problems regarding disclosure that exist in the current weak competition as he said.

on these disclosures if there are reputational, legal and contractual penalties for misreporting; verification of accuracy is costless; or reporting accuracy is supported by guarantees.

Further, Porta et al. (1998) argue that it could be harmful for firms to not follow legal rules because investors may refuse to accept nonstandard contracts. Another related argument made by Bhattacharya (2006) is that ‘if the payoff from cheating is too high and/or private tort and contract litigation is too expensive, there may be a role for public securities laws’ (p. 7). The author suggests that governments can either tighten up their disclosure rules and make deterrent laws by facilitating the process of private enforcement according to the provision of contract law or tort law; or publicly impose securities laws.

A more powerful response to the hypothesis advanced by Coase (1960) and Stigler (1964) is the argument made by La Porta et al. (2006), who contend that, ‘Financial markets do not prosper when left to market forces alone’ (p. 27). In their research paper, La Porta et al. (2006) ask, ‘What works in securities laws?’. They investigate the influence of securities laws on stock market development in 49 countries, demonstrating the positive consequences of securities laws on stock market development and reiterating that securities laws are vital; and providing clear evidence that financial markets do not thrive when left to market forces alone.

In their seminal work, La Porta et al. (1997) investigate empirically how laws that protect investor rights differ among 49 countries and how the quality of enforcement of these laws differs. They use data covering legal rules related to the quality of enforcement and the rights of investors in 49 countries. The authors rank countries based on their legal origin as either common law countries, French civil law countries or German/Scandinavian civil law countries. Their findings indicate that laws differ significantly around the world. For example, La Porta et al. (1997) show that countries under common law protect investors more than so countries under civil law. The authors find that the quality of law enforcement varies considerably among countries, with German and Scandinavian civil law having the highest quality, common law countries following close behind and French civil law countries having the poorest quality enforcement. In a similar vein, La Porta et al. (1999) provide evidence that the performance of a government is driven by the systematic influence of the histories of the relevant country including ethnolinguistic heterogeneity, religion and legal origin; however, it is certainly in part also determined by economic development.

In summary, the structure of legal and regulatory frameworks should be customised to suit the specific requirements and attributes of each nation. This includes considering factors such as the nature and intricacy of its securities markets, the range of financial products and services available and the religious, cultural, social, legal, economic and political context. This section has endeavoured to offer a succinct overview of the literature on the significance of securities laws and their role in economic growth and capital market development. Additional noteworthy aspects are examined in subsequent sections.

4.2.1 Insider Trading Laws

The preceding section provides a general overview of the role of securities laws in promoting the growth and development of financial markets. This section discusses a supplementary dimension of securities laws, specifically emphasising the significance of regulations pertaining to illegal insider trading and enforcement mechanisms. Given the importance of market fairness, efficiency and integrity, market abuse such as insider trading has drawn the attention of policymakers, securities regulators and academics in an effort to learn more about the ways in which insiders can take advantage of legal loopholes and evade prosecution. Therefore, efforts have been increasingly made to establish an equitable market environment in which security trading occurs in a fair manner for all market participants.

Regulation of insider trading has received great interest from researchers seeking to demystify how insiders exploit loopholes in the insider trading legal framework (Aitken et al., 2015; Dalko & Wang, 2016; Karpoff & Lee, 1991; Seyhun, 1992). The prevalence and persistence of insider trading practices, and the legal controversy surrounding some insider trading court cases is a well-researched area that has increasingly attracted the attention of academics, policymakers and securities regulators in an attempt to determine the efficacy of the regulation of insider trading practices and its role in tackling market abuse. The key point is the quality of the legal system that regulates insider trading, alongside the effectiveness enforcement function.

Dalko and Wang (2016) note that over the past half century, insider trading has been observed to exist worldwide despite the presence of legislative regulations prohibiting such conduct and the implementation of laws and enforcement mechanisms, particularly in the US. According to Bhattacharya and Daouk (2002), the first insider trading laws were developed in the US in 1934, and the first enforcement of insider trading regulations supported by modern federal prosecutions occurred in the US in 1961. It has been pointed out that 'insider trading in the capital markets of many other countries historically has been subject either to regulations that have not been enforced or to no regulation at all' (Carlton & Fischel, 1983, p. 860).

The literature survey reveals that insider trading laws exist in the majority of countries, but that enforcement was barely implemented in many countries at the time of the relevant studies (Bhattacharya & Daouk, 2002; Bhattacharya et al., 2000; Fernandes & Ferreira, 2009). In one of the first studies of its kind, Bhattacharya and Daouk (2002) carried out a comprehensive survey of insider trading regulations of all countries that had stock markets at the end of 1998. They examine the existence of insider trading laws alongside their enforcement around the world and investigate whether enforcement of insider trading laws matters. Their survey included 103 countries and reveals that 87 had insider trading laws, yet enforcement as evidenced by first prosecution date had taken place in only 38 countries. The authors note that up to 1990, only nine countries had brought any charges under insider trading laws, and as at the date of the study, Oman was the most recent country to prosecute under insider trading laws, in 1999.

One conclusion from Bhattacharya and Daouk (2002) is that it is enforcement rather than the mere introduction of laws to deter insider trading that plays a pivotal role in insider trading regulation being more effective. In line with this view, Bhattacharya and Daouk (2009) argue, both theoretically and empirically, that for certain types of law such as insider trading laws—particularly in countries where there is less obligation to follow the rule of law—having no law is better than having a strong unenforced law, It can be inferred that the anticipated impact of legislation would primarily manifest when enforcement mechanisms are rigorously implemented, rather than solely through the enactment of the law itself.

In instances where laws are effectively introduced and enforced in a market with a robust legal system, investors will trust that they will receive fair dealings and their rights are well protected by the law. This will motivate outside investors to invest in such a market, even paying more for financial assets because they believe that with a stringent legal system that conserves their rights, more of the company's profits will come back to them as dividends or interest (La Porta et al., 2002). Consequently, investment benefits firms and financial markets become broader and more attractive.

In contrast, in a market where laws are unprotective of investors, the development of financial markets is stunted (La Porta et al., 2006). Kwabi et al. (2018) add that when insider trading laws are weak or insufficiently enforced, investors seek to reduce their participation in such markets, with implications for the cost of equity. Moreover, Chen et al. (2017) find strong evidence that the initial enforcement of insider trading laws is positively associated with capital allocation efficiency.

To enhance the coherence of the argument, strong securities laws serve to protect against unfair practices that may disadvantage external investors, yet the ability of firms to secure funding originates from external sources. According to Bhattacharya (2006), 'Good securities laws ensure that the game is not rigged against outside investors' (p. 5). Moreover, strong insider trading laws entice more foreign investors because they minimise the incentive of controlling shareholders to transfer firm value by trading on inside information (Kwabi et al., 2018). Having introduced the significance of insider trading laws, the following section discusses in more detail the importance and efficacy of enforcement measures.

4.2.2 Enforcement of Insider Trading Laws

The benefits of good securities laws are not limited to the creation of an environment with an optimal legal system without enforcement (Bhattacharya & Daouk, 2002; Chen et al., 2017; Dalko & Wang, 2016; Kwabi et al., 2018). However, the literature well documents the importance of enforcing securities laws because, 'a security law, like any other law, is useless unless it is enforced' (Bhattachrya, 2009).

Carvajal and Elliott (2009) note that the objective of an enforcement program is to guarantee adherence to securities regulation where such regulation, in its entirety, is formulated to promote the development of market fairness, liquidity and stability. Numerous academic studies show the value of well-functioning legal institutions: firms from countries with strong insider trading regulations and stringent enforcement programs have a lower cost of equity, higher liquidity in the capital market, enhanced stock price informativeness and a marked reduction in insider trading activities (Bhattacharya & Daouk, 2002; Dai et al., 2016; Daouk et al., 2006; Fernandes & Ferreira, 2009; Kwabi et al., 2018; Meulbroek, 1992; Ojah et al., 2020).

Furthermore, high-quality institutions and an enforced legal system in a country protects outside investors, attracts foreign investors, reduces risk and lowers information asymmetry (Beny, 2006; La Porta et al., 2002). This in turn promotes investor confidence and fosters participation and liquidity in the stock market (Bhattacharya & Daouk, 2009; Hail & Leuz, 2006). According to Porta et al. (1998), 'Law and the quality of its enforcement are potentially important determinants of what rights security holders have and how well these rights are protected' (p. 1114).

Thus, if laws are properly introduced and effectively enforced, investors believe that their rights are being protected by law, which maintains investor confidence (La Porta et al., 2002, 2006). Conversely, in markets where securities laws are not enforced, investors become aware of the fact that they are at an informational disadvantage and subject to unfair dealings. Thus, investors seek to protect themselves by reducing their participation in the market or demanding a higher return to compensate for the adverse selection risk they experience as a result of information asymmetry, with consequences for liquidity and cost of equity (Adegbite, 2015; Bhattacharya, 2014).

The cost of equity is defined as the required rate of return on an investment (i.e., the return a shareholder requires to decide to owe or hold shares taking into consideration the effect of risk) as explained by Bodie et al. (2019). Bhattacharya and Daouk (2002) document a link between enforcement of insider trading regulations and cost of equity: in their study, the latter decreased considerably from 0.3% to –7.0% as a result of effective insider trading enforcement. Daouk et al. (2006) and Hail and Leuz (2006) support the findings of the relationship reported by Bhattacharya and Daouk (2002).

In the emerging market context, Bhattacharya and Daouk (2009) ask whether the cost of equity increases when a country enacts but does not enforce insider trading laws. They find evidence based on their theoretical model that unenforced insider trading laws increase the cost of equity in emerging markets. Kwabi et al. (2018) analyse a sample of 44 countries over the period 2001–15. Their main hypothesis proposes that rigorous insider trading laws, high-quality institutions and equity portfolio allocation interact to reduce the cost of capital. Based on a difference-in-differences (DiD) model, their findings indicate that a lower cost of capital is found in countries with stringent insider trading laws. With respect to composite impacts of tough insider trading laws, high institutional quality and equity portfolio allocation, the authors find that stringent insider trading law reacts to institutional quality and foreign equity portfolio allocation to lower the country-level cost of capital.

Consistent with the findings of Bhattacharya and Daouk (2002) and Kwabi et al. (2018), Chen et al. (2017) use the DiD approach with a sample consisting of 22,188 firms from 45 countries: 17,924 from 23 developed markets and 4,264 from 22 emerging markets. They find strong evidence that the first action of enforcement of insider trading laws enhances capital allocation efficiency and is positively correlated with liquidity; that is, liquidity goes up surrounding the enforcement year.

Another benefit of enforcement related to private enforcement is the finding of Dai et al. (2016), which is relatively consistent with La Porta et al. (2006), who provide evidence that private enforcement is more effective than public enforcement via mandatory disclosures and liability rules. Dai et al. (2016) demonstrate the beneficial effects of better-governed firms' regulations designed to restrict insiders from misusing private information. They examine the impact of corporate governance systems on the ability of insiders to benefit from private information, and the method by which corporate governance systems influence such practices.

Dai et al. (2016) use a sample of insider trading transactions by companies listed on the New York Stock Exchange (NYSE) and National Association of Securities Dealers Automated Quotations (NASDAQ) from 1998 to 2011. The authors measure the profitability of insider trading by estimating ARs over the 180 calendar days following the insider transaction date. Their findings suggest a reduction in the profitability of insider sales but not of insider purchases, and the abnormal profits earned over the 180 calendar days following the transaction date were significantly lower for insiders of well-governed firms than for insiders of poorly governed firms. They conclude that firms with effective governance systems diminish the ability of insiders to misuse their knowledge of internal information by enhancing the probability of implementing ex ante preventive procedures and conducting ex post disciplinary measures more actively.

This section highlights numerous academic studies showing the significance of enforcing insider trading laws and demonstrates that legislation effects would be expected when enforcement mechanisms are enforced strictly, not merely through the establishment of the laws (Bhattacharya & Daouk, 2009; Cline et al., 2021; Kwabi et al., 2018). The following section provides some information pertaining to measuring enforcement.

4.2.3 Measuring Enforcement

As discussed in the previous section, effective security laws largely depend on a high-quality legal system alongside strict enforcement mechanism. This section seeks to provide more information about measuring enforcement.

Measuring the effectiveness of enforcement is complex because it is difficult to separate the functions of supervision and enforcement. There is implicit and deep-rooted subjectivity associated with the use of several factors, such as the overall assessment of efficient regulatory systems; their contribution to fairness, liquidity and stable markets; and a number of other variables at work in any given measurement (Carvajal & Elliott, 2009). Although financial authorities may believe that plausible deterrence may result in enhancing market participants behaviour because of effective regulation, ‘it can be difficult to identify whether enforcement action is the principal causal factor or whether there are external factors at play’ (IOSC, 2015, p. 51).

Measures used to evaluate quality of enforcement vary among financial regulators. This is exemplified by the work undertaken by Porta et al. (1998) described previously, as well as the later work of La Porta et al. (2006) as discussed in the following paragraph. Before diving into scholarly works pertaining to the metrics of quality enforcement, let us first define common quantitative measures used by regulators in some countries to assess their performance and present reports to government administrators and the public to which they are accountable. These metrics include the number and type of cases filed versus the number of investigations successfully concluded, violators sanctioned, the market cleanliness studies and the number of sanctions enforced (Carvajal & Elliott, 2009; IOSC, 2015)

As a starting point, in their seminal investigation, La Porta et al. (2006) develop a metric of anti-director rights to measure the enforcement of securities laws. The measure is based on invited attorneys' (one from each of 49 countries) responses to a questionnaire. The questionnaire describes several aspects of securities laws and among the variables is a public enforcement metric that is the arithmetic mean of five indices: (1) a supervisor characteristics index (describes the arithmetic mean of one of a majority of the members of the supervisor are not unilaterally appointed by the executive branch, permanency of tenure and focus); (2) a rule-making power index (equals supervisor ability to issue rules without approval from other governmental authorities); (3) an investigative powers index (the arithmetic mean of the ability to ask for documents and call witnesses); (4) an orders index (the arithmetic mean of orders issuer, orders distributor and orders accountant); and (5) a criminal sanctions index (equals the arithmetic mean of criminal director, criminal distributors and criminal accountant).

La Porta et al. (2006) provide some empirical evidence related to private and public enforcement of securities laws. The researchers find little evidence that public enforcement is useful for stock markets; however, there is strong evidence that a system that promotes private enforcement such as mandatory disclosure and transparent liability rules has beneficial effects on financial market development and could work better than public enforcement of securities laws. The findings of La Porta et al. (2006) are in line with those of Porta et al. (1998) and Hail and Leuz (2006), which indicate that the advantages of strong securities regulations emerge from a country's concentration of private litigation, extensive disclosure requirements and market discipline.

In the same vein, a theoretically grounded measure—an anti-self-dealing index—is constructed by Djankov et al. (2008) and calculated for 72 countries. The measure covers both public and private enforcement, with a public enforcement index that combines whether regulators can impose sanctions on a certain insider transaction in terms of fines or jail sentences for the approving body, or for the principal perpetrator. The index of private enforcement includes the approval, disclosure and litigation that govern a certain self-dealing transaction. Generally, this new index helps to better predict a variety of stock market effects relative to the index of anti-director rights proposed by La Porta et al. (2006).

The findings from the study of Djankov et al. (2008) show that the lack of a public intervention approach does not promote more developed financial markets. However, public enforcement plays a crucial role in designing procedure plans to be enforced by private implementation. The authors also suggest some strategies that are in the interests of stock market development, which include outstanding disclosure of self-dealing transactions and facilitating litigation by persecuted shareholders. They find evidence that fines and prison terms imposed by a government authority for self-dealing transactions do not necessarily improve stock market development.

In their wide-ranging study, Daouk et al. (2006) examine the influence of capital market governance on the quality of the stock market in 33 countries. They develop a composite capital market governance (CMG) index using data from individual exchanges in

22 developed countries and 11 emerging markets from December 1969 to December 1998. In addition to the positive effects of enforcement on the cost of equity, the CMG measure captures three approaches to security laws: (1) the enforcement of insider trading laws; (2) the effect of removing short-selling restrictions; and (3) the degree of earnings opacity. They investigate the association between changes in the CMG index and changes in cost of equity (measured by approaches 1 and 2 above); market liquidity (measured by market depth, trading volume and foreign US investments); and pricing efficiency (whether share prices are asynchronous and whether initial public offerings are under-priced). The interesting findings from their measures indicate that efficient security laws are associated with reductions in the cost of equity capital, increases in market liquidity and increases in market pricing efficiency.

Further to this, the work of Hail and Leuz (2006) builds on the finance study of La Porta et al. (2006) related to the role of legal institutions, with findings consistent with those of Bhattacharya and Daouk (2002) and Daouk et al. (2006). Hail and Leuz (2006) use the metric developed by La Porta et al. (2006) to measure the enforcement of securities laws. Hail and Leuz (2006) investigate international differences in the cost of equity capital across 40 countries from 1992 to 2001. The authors ask whether the effectiveness of securities regulations and legal institutions is systematically associated with companies' cost of equity. Among their broad suite of variables covering legal institutions and securities regulations is the enforcement of securities laws. They use several models to evaluate companies' implied or ex ante cost of capital in an analysis concentrating on regulation mandating and enforcing disclosure. Their results reinforce that those nations with the most rigorous securities regulations, strong enforcement mechanisms and comprehensive disclosure requirements have lower cost of equity.

Although some of the measures discussed so far assess the enforcement of insider trading laws in general terms, the discussion now turns to the MCMs, the metrics utilised in the present study to evaluate the efficacy of enforcing insider trading regulations. These measures are particularly relevant to the primary aim of the present investigation, which is to assess the impact of the regulations introduced with recent financial reforms on the level of potential insider trading activities. As pointed out earlier, MCMs have been extensively applied in academic and regulatory settings to examine legislative changes with a focus on estimating potential instances of insider trading and information leakage ahead of material price-sensitive announcements (e.g., ASIC, 2016, 2019; Dubow & Monteiro, 2006; Goldman et al., 2014; Hensen, 2018; Monteiro et al., 2007; Nagata, 2017).

For instance, the UK FCA (formerly the FSA) employs the MCMs proposed by Dubow and Monterio (2006) to examine the impact of the FSMA on the level of insider trading before and after the enforcement of this act. The FCA has conducted several market cleanliness studies for firms listed on UK securities markets and published annual updates to the MCMs over the last two decades (Dubow & Monteiro, 2006; Goldman et al., 2014; Monteiro et al., 2007). Similarly, the ASIC (2016, 2019) has applied the MCMs to assess the cleanliness of Australian equity markets after the transfer of market supervision. Along similar lines, Hensen (2018) assesses the cleanliness of New Zealand equity markets from 2010 to 2016 using the MCMs.

Therefore, as the present study aims to examine the impact of regulatory changes introduced with financial reforms on the level of potential insider trading on the Tadawul, the MCMs are considered an appropriate method that serves the purpose of this research. Several additional factors motivate the use of such measures. First, the MCMs are considered as a measure of whether insider trading rules and fair disclosure are complied with. According to Carvajal and Elliott (2009), ‘Market cleanliness studies measure the whole effect of a compliance program, not only of the enforcement (sanctioning) function’ (p. 32). The authors note that such studies provide important insights into the effectiveness of enforcement.

Second, the approach lays the groundwork for monitoring the effectiveness of new regulations in deterring insider trading and improving corporate disclosure in a regulatory environment.

Furthermore, studies provide important insights into the link between insider trading activities and the performance of stock returns and trading volumes. To be more specific, numerous scholars and financial authorities find that ARs or abnormal trading volumes preceding major corporate events are indicative of substantial news about share value and, thus, serve as indicators of information leakage and suspicious activities related to insider trading. A necessary condition to assess the occurrence of potential insider trading activities is, therefore, the detection of ARs and AVs ahead of corporates events.

The third rationale reason for the use of the MCMs is their efficacy as a tool for defining the ratio of firms events for which significant abnormal movements in share prices or trading volumes were detected before the release of corporate announcements. IOSC (2015) assessors identify key elements of measures that regulators may be considering, which include observable data (analysis of price and volume movements surrounding event dates), feedback (collecting information by asking people how the regulator is performing), media mining (measuring media reaction) and econometric modelling (using mathematical and statistical tools to predict market conditions).

The MCMs involve statistical procedures that align with the well-known event studies approaches to estimate the level of possible insider trading activities by determining the proportion of SAs that were preceded by APPMs and APAVs. The SAs, APPMs and APAVs are estimated using the widely recognised event study methods and employing a verity of econometric models. According to Bodie et al. (2019), 'evidence of leakage appears almost universally in event studies, suggesting at least some abuse of insider trading rules' (p. 361).

Moreover, Binder (1998) suggests that the event study method has emerged as the prevailing approach for assessing the extent to which security prices respond to specific events.

In summary, drawing on the review presented in preceding sections, this section culminates in the formulation of the first two main hypotheses for the research. The above discussion encompasses a multitude of scholarly investigations that present evidence indicating that nations with more stringent regulations on insider trading and robust enforcement mechanisms have achieved notable success in reducing insider trading activities. The amended regulatory changes instituted by the Saudi CMA were created to strengthen the MCR, combat market misconduct, build investor confidence and further align the market condition with international standards.

The effects of these amendments on potential insider trading practices are assessed here by estimating and comparing the Tadawul's MCMs before and after the introduction of regulatory changes. The statistical significance of the difference is investigated against the null hypotheses of no significant changes in the ratios of the MCMs for the stock returns and trading volumes event studies analyses between both periods. This leads to formulation of the first (MH_{01}) and second main hypothesis (MH_{02}) of this study, expressed in the null form as follow:

MH_{01}: The level of potential insider trading of the returns event study MCMs is not significantly lower after the introduction of financial reforms.

MH_{02}: The level of potential insider trading of the trading volume event study MCMs is not significantly lower after the introduction of financial reforms.

4.3 Methodological Review of the Event Study Approach

This section presents a comprehensive review of event study methodologies in the finance literature. The event study method in the finance discipline involves a type of empirical financial research that empowers a researcher to assess how a certain event would affect a specific financial variable, such as stock returns or trading volumes (Brook, 2019; Brown & Warner, 1980; MacKinly, 1997). In addition to their common usage in financial economics, event studies are used in various research areas such as medical and health (Gupta et al., 2021; Powell et al., 2018), the management sector (Kim et al., 2020; Maneenop & Kotcharin, 2020), the marketing industry (Stoker et al., 2019) and law to examine the effects of changes in law policies and regulations (Mitchell & Netter, 1994; Wilf, 2016; Zeng, 2021). The following section extensively reviews the returns event study approach.

4.3.1 Returns Event Study Approach

Over the last six decades, event studies have been widely used and have made an important contribution to capital market studies. Even studies have been a useful tool in empirical research as they serve as an exemplary instrument for evaluating the information content of disclosures to gauge the impact of events on firms' market values (Brooks, 2019; Campbell et al., 1998; Kothari & Warner, 2007). MacKinly (1997) suggests that the idea of the event study method was first proposed by Dolley (1933), who investigated the impact of stock splits on security prices. The primary framework for undertaking classic and contemporary event studies was developed by Ball and Brown (1968) and Fama et al. (1969). Ball and Brown (1968) test the information content of earnings announcements, and a methodological revolution was pioneered by Fama et al. (1969) who examine security price behaviour around events such as accounting rule changes and earnings announcements. Expansions of the methodology in the literature largely focus on improving robust inference methods (Brown & Warner, 1980, 1985; Corrado, 1989, 2011; Elsas & Schoch, 2023; Sun & Abraham, 2021).

Binder (1998) points out two factors driving the use of the event study method. The first pertains to the examination of publicly available information to assess the impact of a particular event on the financial worth of companies. Second, the method serves a crucial role in capital market research as a way to test market efficiency (Brown & Warner, 1980; Fama, 1991; Heyden & Heyden, 2021; Syed & Bajwa, 2018). In the context of market efficiency, the method is used to test the EMH regarding the extent to which information is efficiently and quickly incorporated into security prices (supplementary clarification is provided in Section 3.3.4, which presents a comprehensive discussion of the EMH with reference to a number of empirical studies).

Briefly, the benefit of the event study approach lies in its advantage of being a valid and robust technique for testing the EMH. This hypothesis relies on the assumption that the effect of a given event will be rapidly mirrored in security prices soon after news announcements. This is because security prices are only adjusted effectively in response to new information when significant ARs abound (MacKinlay, 1997). Market efficiency, which can be measured using the event study method, is violated when non-zero abnormal stock returns exist around a particular event being investigated. As discussed in Section 3.3.4, the market can detect insider trading activities because the practice incorporates the information into the stock price. This case pertains to the strong form test of the EMH, which test whether certain investors or groups have privileged access to relevant information that influences the price process (Fama, 1970).

The event study method is established in the literature as a functional tool that helps capture the extent of significant abnormal movements in share prices or trading volumes prior to firms announcements, which are likely to be driven by insider trading. As this study aims to estimate the level of potential insider trading on the Tadawul before and after introduction of regulatory amendments instituted with financial reforms, the event study MCMs is employed. The event study approach is used to probe the existence of abnormal movements in stock prices and volumes prior to the disclosure of companies announcements and market cleanliness is used to determine the proportion of SAs that were preceded by APPMs and

APAVs. Examples of firms events include takeover, mergers, acquisitions and other material price-sensitive announcements (see Section 5.2).

The next sections proceed to outline common practices in the finance literature pertaining to the structure and approaches to the event study method. Briefly, according to the methodological framework proposed by MacKinlay (1997), empirical procedures typically involve implementing seven key steps to give confidence in the inferences drawn. The first step is to determine a clear definition of the event date and specify suitable lengths for the event and estimation windows under investigation. This step includes clear explanations that justify the event window lengths selected. The second step is to establish criteria for selecting relevant data on firms events and their associated financial variables (discussed in detail in Section 5.2.3). The third step is to choose an appropriate model for estimating the impact of the event on ARs and abnormal trading volumes. This is followed in the fourth step by estimating the parameters of the chosen models. The fifth step is to design a framework for hypothesis testing via statistical tests. The sixth step involves presentation of the empirical findings. The seventh step is to discuss interpretations and draw conclusions based on the results obtained. These steps are implemented in this research and discussed in detail in the following sections with reference to studies that have employed diverse techniques.

4.3.2 Identification of the Horizon Length for Event and Estimation Windows

In practical applications, the conventional event study method typically starts by identifying the time parameters. This task involves partitioning the observation period into two distinct intervals, where the first is the estimation window and the second is the event window. The event window is divided into pre- and post-event windows. This section delineates the methods and factors that should be considered to select appropriate lengths for these windows.

Scholars of landmark and systematic reviews of event studies strongly emphasise that when employing an event study method, caution is required in the research design. It is essential for researchers to provide justification for their chosen window lengths (Bouzzine, 2021; McWilliams & Siegel, 1997; Sorescu et al., 2017). Therefore, this study considers key rules when determining the lengths of these windows to ensure use of the best estimation techniques and increase the robustness of inferences.

The initial step in an event study involves accurately defining the event of interest being examined and designing the event window with respect to the event date, to gauge the impact on security returns of the arrival of information associated with the event (Brooks, 2019; MacKinlay, 1997). The event window length is the most crucial choice to be made and poses a major challenge because multiple factors may have a significant impact on the statistical properties of event study analysis (Flammer, 2013). These factors include horizon length, market characteristics, insider trading patterns, security volatility, sample size, the procedures of modelling ARs or abnormal trading volumes, and statistical tests.

Regarding the first aspect pertaining to the horizon length of the event window under examination, it is useful to present definitions for a long versus short horizon window before outlining their characteristics, to establish a foundation for later discussions. The delineation of a long horizon may lack precision, but it typically encompasses event windows spanning one year or longer (Kothari & Warner, 2007). In contrast, a short horizon window is taken to be a few days around the event day; commonly 10 trading days before and up to 10 days after (Brook, 2019). MacKinly (1997) uses a short event period consisting of 20 trading days for the pre-event window and 20 trading days for the post-event window.

However, there is a trade-off in selecting a long versus a short horizon. Several factors necessitate extreme caution when it comes to selection of the event window length. The first is the legal framework of the market system. The second is the behaviour and tactics of insider traders. The third relates to the statistical properties of the event and estimation windows. These aspects are explicated in depth the following seven sections.

4.3.2.1 The Legal Framework of the Market System

With respect to a market's legal system, disclosure regimes involving policies and rules that govern the timing of release of official announcements differ among countries. Determination of the appropriate duration for the event window considering the legal framework of the market is contingent on two distinct scenarios. First, in markets with poor disclosure regimes, an official announcement is likely to be made at a later stage of negotiations following submission of a formal offer (Goldman et al., 2014). This long duration may allow insiders to strategically expand their trading activities (Biggerstaff et al., 2020; Fu et al., 2020), thereby mitigating any effects on stock prices resulting from their trades. Under this circumstance, a very short window may fail to precisely capture ARs and abnormal trading volumes, which might lead to false inferences about the significance of the event being tested.

Conversely, the second scenario pertains to a market in which it is mandatory to disclose information to the public at an early stage, frequently preceding formal bids. In this case, there is a narrow window for insiders to exploit inside information and conduct trading. As discussed in Chapter 2, Bhattacharya et al. (2000) presents empirical evidence that corporate announcements do not have a significant impact on prices because instances of information leakage occur far in advance of the official announcement. However, given that the first scenario is unlikely to be true for the Tadawul, there is no concern about the selection of a short event window after considering the market disclosure regime.[27]

[27] It is a regulatory requirement for all publicly traded companies listed on the Tadawul Stock Exchange to promptly and accurately disclose any information that could potentially influence the value of their stocks. See Chapter 2 for further information.

4.3.2.2 Trading Strategies Used by Insider Traders

The strategic timing of insider traders is a source of concern when it comes to the selection of the event window length. The research literature theoretically and empirically documents the proficiency of insider traders in camouflaging and concealing their activities by strategically timing their trades relative to the event date (Davis et al., 2020; Katselas, 2019; Keown & Pinkerton, 1981; Kyle, 1985; Suk & Wang, 2021), executing gradual stock purchases or sales to mitigate the impact on stock price movements (Ahern, 2020; Collin-Dufresne & Fos, 2015), employing extensive use of limit orders when public disclosure is not imminent (Bolandnazar et al., 2020; Collin-Dufresne & Fos, 2016), spreading their trades across a longer horizon when they have longer-lived information, and trading over a shorter horizon duration when their informational advantage is short lived (Biggerstaff et al., 2020).

Under these circumstances, even if insider trading is taking place, it is a challenge to determine an appropriate event window length. Kothari and Warner (2007) point out that even if announcement dates are well defined, instances of insider trading may take place over one month. The authors add that unlike a short event window, a long event window typically provides limited statistical power in detecting abnormal movements, regardless of whether they are concentrated into the event window. However, such challenge would be mitigated when considering the other factors associated with statistical issues of the event window horizon which strongly support the chosen length in the current study.

4.3.2.3 Statistical Properties of the Event Window Length

The third decision regarding a suitable event window length is based purely on statistical choices. A number of the empirical finance literature demonstrate that the use of a long event window raises major concerns which might make it harder to draw reliable statistical inferences (Brown & Warner, 1980; Campbell et al., 1998; Flammer, 2013; Kothari

& Warner, 2007; McWilliams & Siegel, 1997). Although there have been improvements in long horizon methods (for more detail see Brav, 2000; Lyon et al., 1999), significant limitations persist. Fama (1991) notes that the interpretation of long event window results is not free of problems and that short window tests provide the cleanest evidence of market efficiency. Inferences based on long window tests should be interpreted with great caution because a skewness bias emerges from the distribution of ARs in a long event window (Kothari & Warner, 1997).

Surprisingly, even when employing the most reliable methods, the analysis of long-run ARs is considered risky and may result in mis-specified statistical tests as demonstrated by Lyon et al. (1999). These issues highlight and strongly reinforce cautions raised by Brown and Warner (1980) regarding the lower reliability of the long event window method. In alignment with Brown and Warner (1980), Campbell et al. (1998) note that employing a long event window severely weakens the power of statistical tests, which may lead to false inferences.

It is empirically documented that a short event window typically captures the significance of an event (Flammer, 2013; Ryngaert & Netter, 1990). In line with this view, Kothari and Warner (2007) state that it is reasonable to place greater confidence and importance on outcomes derived from a short event window than those from a long event window. The authors further indicate that a short event window is straightforward, characterised by relative simplicity and devoid of risks. Given concerns related to a long event window, empirical studies may be more robust when implementing a short window method.

However, it is worth noting a possible drawback with a very short event window that is defined in the finance literature as an uncertainty event, in which the announcement publication date is not the actual event date of interest. This issue may become a source of concern when using an extremely narrow event window, such as a one-day interval, but can be addressed by extending the event window to more than one day (Flammer, 2013; McWilliams & Siegel, 1997).

This problem does not raise concern in the current study for two reasons. First, multiple event window lengths are used. In robustness checks, Flammer (2013) uses three-, four- and five-day windows and provides empirical evidence that the findings using such short windows are robust. Ball and Torous (1988) thoroughly consider inherent uncertainty in the dates of events and provide empirical evidence that use of multiple event window lengths provides robust results. Second, care in exercised in this study when defining the event day if the announcement is made after the close of the market. The event date is manually documented with millisecond precision, which involves not only considering the date of the announcement but specifying the precise time at which the announcement was released (see Section 5.3).

4.3.2.4 Confounding Event Effects

Another issue to consider when selecting the event window length is the problem of confounding events. This relates to the case in which a company discloses multiple major events on different days within the event window being tested. Notably, the method employed in the present study assumes there are no confounding events within the event window. Therefore, use of a long event window would be more likely to increase the probability of capturing confounding effects, leading to false inferences (Bouzzine, 2021; Flammer, 2013; McWilliams & Siegel, 1997).

To minimise the potential for such problems, employing a short event window is a safer approach to prevent contaminating events (Flammer, 2013). Sorescu et al. (2017) and Bouzzine (2021) suggest that using a relatively short event window is beneficial in effectively mitigating the effects of confounding events. McWilliams and Siegel (1997) indicate that examinations with longer event windows necessitate extensive research to effectively treat potential confounding events. The authors recommend using an event window as short as possible, arguing that the adjustment of stock prices to new information may be complete within a few hours or even minutes.

In contrast, using a long window will more likely exacerbate the issue of handling the influence of confounding events within the event window (Aktas et al., 2007). Some studies exclude all companies associated with confounding events during the event window (Koppenberg et al., 2023; Minefee et al., 2021; Pandey & Kumari, 2021). Sorescu et al. (2017) suggest that confounding observations should not on average impact estimations over short windows, which renders the elimination of such events unnecessary. McWilliams and Siegel (1997) claim that excluding confounding events is a drastic approach that dramatically reduces the sample size. The authors argue that it is possible that the existence of this problem may provide significant information on confounding effects. As previously mentioned, the current study addresses the issue by hand-collecting data to ensure there are no confounding events within the event window.

Another potential concern that may arise when estimating ARs over a long event window pertains to the underlying assumption of the market model utilised in the present study. This assumption is based on ordinary least squares (OLS) regressions, which assume that the α and β parameters remain constant over the event window (Aktas et al., 2007; McWilliams & Siegel, 1997). Unlike a long horizon event window, 'over short windows, discrepancies between models are usually small and any errors in model specification are almost negligible' (Brook, 2019, p. 643). Brown and Warner (1985) note that the models they use, including the market model, perform very well over short windows as the expected returns are close to zero, while long windows raise critical issues.

This discussion concludes the most important points in the selection of the event window length. Before disclosing the choice of event window length (provided in Section 4.3.2.7), it is important to shed light on the statistical properties of the estimation window size.

4.3.2.5 Statistical Properties of the Estimation Window Length

The factors discussed so far are relevant to the duration of the event window, and strongly justify the use of a short event window; however, there are other considerations. The mechanical selection of the estimation window length is not devoid of complexity. Subjective selection may introduce biases when estimating model parameters and thus undermine the statistical conclusions (Jeng & Jeng, 2020b). Thus, it is necessary to specify a length of estimation window considering factors that may negatively impact model estimation. In general, the choice of the estimation window length may rely on the model chosen to estimate the abnormal performance, the effect of time-varying conditional volatility, serial correlation and overlapping events. The potential presence of these features is thoroughly examined in this thesis.

The estimation window is defined as the period preceding the event window and is used to estimate the model parameters. The choice of the length of the estimation window is often arbitrary (Bos et al., 2019). In a systematic literature review of event studies from 1990 to 2020, Bouzzine (2021) notes that heterogeneity is evident among researchers in the definition of estimation windows. Peterson (1989) suggests that determination of the length of the estimation period is at the discretion of the researcher, but there is a need to balance the benefits of a longer period—such as an improved prediction model—with the drawback of potential instability of model parameters. Such issues have been considered in the current study.

Armitage (1995) and Peterson (1989) suggest that the length of the estimation period can range from 100 to 300 days before the event window is the analysis is based on daily observations. Similarly, Aktas et al. (2007) note that in event studies using daily data, it is common practice to select a time frame ranging from day −250 to day −30 in relation to the event date. In their event studies, MacKinlay (1997), Bhabra and Hossain (2015) and Lagasio and Brogi (2021) use estimation windows lengths of 250, 253 and 252 trading days, respectively. It is worth emphasising that longer estimation windows are likely to aggravate issues related to data characteristics; that is, contaminating events that may overlap the estimation window. The final issue that should be recognised when choosing the estimation window length is overlapping events.

4.3.2.6 Treatment of Overlapping Events

Overlapping events occur when multiple announcements are published by the same firm during the estimation window. If such events are frequent, they may influence the overall estimation of ARs or AVs (Brown & Warner, 1980; MacKinly, 1997). Several propositions have been advanced to remedy such potential problems and enhance the fundamental empirical methodology.

First, data characteristics may have influence the process of modelling ARs as the estimation uses daily data for the estimation window. Studies note that failure to account for the impacts of thin trading, autocorrelation or event-induced variance (volatility) may lead to erroneous identification of hypothesis tests (Brown & Warner, 1985; Scholes & Williams, 1977). The challenges associated with these issues can be mitigated by implementation of model selection tests (Harrington & Shrider, 2007; Jeng & Jeng, 2020a). Accordingly, the current study considers four scenarios to handle issues associated with the nature of data by employing a diverse array of advanced models and diagnostic tests. These choices are driven by the data characteristics observed in the sample under study and align with previous studies (Section 5.5 provides a detailed explanation for the inclusion of several methods).

Second, although the measures are not limited to use of several sophisticated models, other caveats concerned with overlapping events in the estimation window have been considered. In their review of event studies, Sourse et al. (2017) find that 21 of 42 studies eliminate overlapping observations from their sample. As noted earlier in the discussion of event window length, while this approach may address the problem, it reduces the sample size. Another procedure to mitigate this problem involves shortening the estimation window length for events that experience overlapping. Although one may argue that the most appropriate estimation window length is not identical throughout the sample being analysed, research suggests that use of a bootstrap approach will handle the issue (Aktas et al., 2004; Brooks, 2019).

The present study considers use of bootstrapping, which deals with non-normally distributed returns data in event studies. It generates an empirical distribution by estimating the sampling distribution using random sampling techniques with replacement from the actual data. Other tests, including that of Boehmer et al. (1991) as well as nonparametric tests (e.g., Wilcoxon) alongside bootstrapping are employed by Ferretti et al. (2019) who note that their findings are similar for the three tests. The bootstrapping technique is investigated and recommended in a number of studies (e.g., Chou, 2004; Gelbach et al., 2013; Hein & Westfall, 2004; Kramer, 2001; Kurek, 2016).

Following Monteiro et al. (2007), the current study uses bootstrapping with minor amendments for the purpose of handling overlapping events, by performing two procedures. First, an event adjustment procedure is introduced to handle the effects of overlapping events during the estimation window. For example, in an event window length consisting of five trading days, the procedure performed involves substituting the previous five observations that overlap in the estimation window with five observations from historical data. Note that the magnitude of the replaced values across the estimation window is the same as the event window size, which includes the day of the event, two days before and two days after the event day. The overlapping events that fall within the estimation window are not excluded because this causes the estimation window to be shorter for events that have experienced overlapping events. This approach is deemed capable of mitigating the possible effects of overlapping events during the estimation window and maintaining the length of the estimation window to be identical to its specified length of 240 trading days for the whole sample.

The second procedure relates to the mechanics of the bootstrap method. The resampling approach is based on large numbers of samples of the same size as the sum of ARs that are randomly drawn and repeated 50,000 times with replacement from the original sample of ARs. This reduces the existence of outliers. Brook (2019) notes that the problem of outliers such as very high returns over the estimation window period affects market model parameter or residual variance estimation. The author suggests using the bootstrap method to calculate test statistics to tackle this problem.

Repeated random sampling 50,000 times with replacement may select some values already captured by previous bootstraps. Therefore, the ‘set seed technique’ is applied, which allows for resampling without drawing and summing the values of resampled ARs. These procedures make a valuable addition and are discussed in more detail in Chapter 6. The preceding sections discuss factors relevant to selection of event and estimation window lengths. The following section specifies the window lengths selected for this study.

4.3.2.7 Position and Length Selected for Event and Estimation Windows

After conducting an extensive review of the literature examining a broad variety of issues related to the lengths of estimation and event windows, this section explicitly specifies the carefully selected lengths for this study. The estimation window is determined to begin one year before the event window. Specifically, for each event, the precise length of the estimation window is 240 trading days, stopping 10 trading days prior to the event window (–250 to –11). Werner (2017) notes that estimating the market model (as used in the current study) over an extended estimation window—such as a year and half prior to the event—provides a sufficient distance between the estimation and event windows. Brook (2019) indicates that the precision of parameter estimation increases when long estimation windows are used. Moreover, the length selected for the estimation window is consistent with previous studies (Goldman et al., 2014; Monteiro et al., 2007; Ullah et al., 2021).

The review conducted on the determination of the event window length suggests considerable credibility of empirical results using a short event window method. It is evident that the use of a long event window severely reduces the statistical power of event study tests (Brown & Warner, 1985; Fama, 1991; Kothary & Warner, 2007) as it gives more space for insiders to expand their trading activities (Biggerstaff et al., 2020) and increases the probability of capturing confounding effects (Aktas et al., 2007; McWilliams & Siegel, 1997; Sorescu et al., 2017). Therefore, selection of a short event window length for the present study is justified.

A robust short window approach relies on a precisely specified event date as well as the pre-event window being placed before the announcement to cover the period during which potential insider trading is expected to occur, so that the associated ARs can be captured (Campbell et al., 1998; Kothari & Warner, 2007). The choice of the post-event window length is less problematic because it only must be long enough for new information to be incorporated into the stock price (McKinly 1997; McWilliams & Siegel 1997). These conditions have been carefully maintained in the present study. Nevertheless, determination of the duration of the event window is differs in some respects from previous market cleanliness studies, motivated by the review and the multiple reasons outlined below.

First, studies employing the event study market cleanliness method use different event windows to capture abnormal price reactions prior to the event date. Two recent studies conducted by the ASIC (2016, 2019) use a five-day event window. Three earlier event studies by Dubow and Monteiro (2006), Goldman et al. (2014) and Monteiro et al. (2007) each use a two-day event window. These studies justify their selected lengths based on the experience of their regulatory authority enforcement and surveillance specialists. However, such an extremely narrow (two-day) window may not capture all instances of insider trading because it starts too late and ends too soon.

Second, in addition to central factors discussed in the aforementioned survey of literature that justify our choice of event window length, a very short event window length such as two days may not account for possible information leakage or instances of insider trading activities in the Tadawul. As discussed in Chapter 2, Syed and Bajwa (2018) conduct an event study using an event window of 21 trading days to test the EMH in the Tadawul. They observe significant and positive ARs in favourable of good news trend particularly from day -9 to day -4 within the pre-event window. Thus, employing a single length identical to that used in previous market cleanliness event studies may lead to misleading outcomes.

Third, in a systematic review conducted by Bouzzine (2021), 21 of 17 event studies use only a single event window to analyse the market reaction to an event. However, the author argues that stock price reactions are not necessarily limited to a single window, and recommends the use of multiple event windows, ‘that would enable the capture of potential information leakage, investors anticipation and delayed learning effects’ (p. 12). Finally, the present discussion highlights the robustness checks carried out by Flammer (2013) and Ball and Torous (1988), both of which offer empirical evidence for the robustness of using multiple event window lengths.

Therefore, multiple event window lengths are used in the present study—(–2, +2), (–5, +5) and (–10, +10) days around the event—instead of an event window with a single length. Conducting the analysis in this way helps to determine the optimal window length for detecting ARs. It also enhances the study's application of the market cleanliness method and explores the most suitable event window length for the Tadawul. This decision assumes that it will not significantly affect the MCMs. Hence, the null hypothesis is that:

H_{03}: The difference in the MCMs between the two periods is insignificant regardless of the length of the event window.

4.3.3 Models for Estimating Abnormal Returns

As mentioned in Section 4.3.1, the event study design involves seven steps. The preceding section comprehensively examines key aspects associated with the initial task of identifying elements of the event day as well as the length of the event window and the estimation window. This section describes selection of a suitable model for estimating the ARs. It is important to note that the current study uses an event study method with both price and volume data. This section surveys the returns event research literature and the literature on trading volume event studies is reviewed in Section 4.3.6.

As previously stated, a returns event study gauges the impact of a certain event on a security return surrounding an event that conveys new information. The ARs are defined as the difference between the actual and expected returns conditional on the absence of the event effect under investigation. To identify ARs, it is necessary to first establish a model of expected returns (i.e., normal returns), which can be obtained using an appropriate benchmark asset pricing model. The following discussion briefly reviews several models and provides a summary of their respective predictions. Further elaboration on the specifications and calculations pertaining to the chosen model can be found in Chapter 5.

Various asset pricing models have been used in event studies to estimate expected returns, including the market model, constant expected returns model and capital asset pricing model (CAPM). Despite the existence of more contemporary multifactor models—such as the Fama and French (1992) three-factor, Carhart (1997) four-factor and Fama and French (2015) five-factor models—a systematic review conducted by Bouzzine (2021) reveals that the market model is the most commonly employed benchmark in event studies, even the most recent event studies in finance (El Badlaoui & Cherqaoui, 2023; Koppenberg et al., 2023; Pandey & Kumari, 2021; Zeng, 2021).

Although the CAPM was commonly used in event studies during the 1970s, the conflicting findings from various studies increase doubt about the CAPM's validity (MacKinlay, 1997). MacKinlay indicates that departures from the CAPM have been identified, suggesting that the reliability of limitations imposed by the CAPM on the market model is a matter of concern given that the outcomes of studies could potentially be sensitive to the CAPM. Because this potential for sensitivity can be avoided at little cost by using the market model, the use of the CAPM has almost ceased' as explained by (MacKinlay, 1997, p. 19).

The CAPM has been extensively criticised and discredited because of substantial evidence of anomalies (Kothari & Warner, 2007). Fama and French (1996) offer a detailed discussion of the shortcomings associated with the CAPM's average return anomalies. Van Binsbergen and Koijen (2017) find that the CAPM fails in two significant respects: the equity risk premium and excess volatility. Fama (1973) points out that the relationship between the market model and the two-parameter model—the linear regression coefficient β—is like the risk measure β of the two-parameter model. Likewise, Stapleton and Subrahmanyam (1983) indicate that a risk measure of the market model β is comparable with the CAPM.

Regarding multifactor models, event studies are joint tests of the validity of the chosen model of expected returns, data frequency, event window length, confounding events and statistical tests. The potential benefits of using multifactor models in event studies are small, as indicated by MacKinlay (1997). The author states that empirical evidence suggests that the inclusion of additional factors has limited explanatory power in terms of marginal effects; hence, there is minimal reduction in the variance in ARs.

Sorescu et al. (2017) indicate that the Fama and French (1992) three-factor model and the Carhart (1997) four-factor model have been used to estimate ARs in monthly databases over long horizon windows (>342 months in the case of Fama and French). Sorescu et al. (2017), however, point out that statistical properties as a foundational approach for short horizon event studies are yet to be broadly validated. Thus, as previous work using these models was conducted over long horizon windows and based on monthly observations, the present study employs a short horizon method and daily data. Kothari and Warner (2007) argue that the use of monthly data across a long event window raises concerns of autocorrelation in time series because of overlapping return data.

Further, as discussed above, as event studies are joint tests, the aforementioned factors can have a major impact on the characteristics of the AR measure. Before discussing the relevant factors here, it is necessary to go back to the implications of the event window length (see Section 4.3.1) with a particular emphasis on its impact on the choice of the expected return model and test statistic. Kothari and Warner (2007) report that the test statistic specification in short event window methods exhibits low sensitivity towards the benchmark model of expected returns and assumptions regarding the cross-sectional or time series dependence of ARs. This stands in contrast to a long event window approach where the model specification is highly sensitive to assumptions concerning the process of modelling ARs, as noted by the authors. Brav (2000) argues that the reason for the statistic test mis-specification may be the tendency for researchers conducting long horizon tests to uphold the standard assumption that ARs are independent and normally distributed, although these assumptions do not apply to a long horizon event window.

Considering the foregoing discussion, the current study selects a benchmark model in line with the chosen event window length. Moreover, given that the present research employs the MCMs for a different market (the Tadawul), it strives to extend previous market cleanliness event studies with minor changes. Therefore, it may be conjectured that if a wider range of modifications had been employed, the MCMs may be influenced significantly, particularly if using multifactor models. In any case, it is beyond the scope of this study to apply the method with major changes.

Among other statistical models, the constant mean return model and the market model are widely used in event studies. These two models demonstrate sufficiency in terms of the distributional assumption that asset returns are independently and identically distributed (IID) over time (Brown & Warner, 1985; MacKinlay, 1997). However, the market model offers a potential enhancement over the constant mean return model through the elimination of the return ratio linked to market return variation, which reduces the variance in ARs (MacKinlay, 1997). (Strong, 1992) comments on the advantage of the market model indicating that ‘it results in smaller variances of ARs (relative to raw returns), leading to more powerful statistical tests’ (p. 538). This feature motivates the use of the market model in this thesis.

The validity and reliability of the market model is established by the seminal work of Brown and Warner (1985). In both early and more recent event studies, researchers commonly employ a straightforward and simple method, the single-index market model, to identify a benchmark of normal return (Bouzzain, 2021; Secourc et al., 2017). The market model has been widely utilised in the context of emerging markets, developed markets and multi-country studies (Campbell et al., 2010; El Badlaoui & Cherqaoui, 2023; Lagasio & Brogi, 2021; Scholtens & Oueghlissi, 2020; Strong, 1992; Yousaf et al., 2022).

Accordingly, the daily abnormal stock returns are estimated in the current study by employing a standard event study method involving the market model, which relates the return of a stock to the market portfolio return following Browen and Warner (1985), MacKinly (1997), Dubow and Monteiro (2006) and Monteiro et al. (2007). The market model is used to identify ARs, as it calculates the statistical relationship between an individual firm's return and the return of the broad market index over the estimation window (−250, −11). The ARs are computed as the difference between the expected return and the actual return. The cumulative abnormal returns (CARs) for the security are calculated by summing the ARs over the event window being examined. Bootstrap test statistics and quantile thresholds are used to assess whether the distribution of the CARs during the event window is statistically significant.

The MCMs of the return event study can be estimated from the ratio of APPMs observed before the SAs. Section 5.4.3 describes the techniques used to determine if an event is a SA and is preceded by an APPM. Briefly, the presence of significant CARs over the post-event window implies that an announcement contains important news and should be considered a SA, and significant CARs across the pre-event window are an indicator of the occurrence of APPMs. In contrast, an event is not considered a SA if no statistically significant CARs are detected over the post-event window being examined. Therefore, the null hypothesis to be tested is that:

> H_{04}: The announcement had no significant impact on the distribution of CARs over the post-event window.

Thereafter, if the event is found to be a statistically SA, a necessary condition to assess if the APPMs have not taken place before the SA is the absence of significant CARs across the pre-event window, as proposed in the following null hypothesis:

H_{05}: The announcement had no significant impact on the distribution of CARs over the pre-event window.

This concludes the presentation of the market model in its basic version. However, the purpose of this section is to serve as a starting point for examination of other statistical assumptions. The discussion now turns to various extensions and refinements to the market model for more robust estimation.

4.3.4 Modelling Abnormal Reruns in the Presence of Volatility and Serial Correlation

The preceding section discusses the estimation of ARs using the conventional market model. However, the standard market model may not satisfy the assumption of constant error variance or serial correlation. Therefore, this section considers advanced modelling approaches to overcome the problems of heteroscedasticity and seral correlation.

Early event studies provide empirical evidence of a significant increase in stock return variance on the days surrounding event days involving earnings announcements (Beaver, 1968; Brown & Warner, 1985). Rosenstein and Wyatt (1990) observe that when certain events happen in a firm, the variance in returns increases significantly. Brown and Warner (1985) investigate the extent to which the characteristics of time series data with daily security return affect the event study approach. They find that the variance in the sample mean excess return doubles on the event day. Gujarati and Porter (2009) note that the estimators and standard errors of OLS are sensitive to small changes in the data.

The increasing variance issue has a direct impact on the specification of test statistics frequently employed in traditional event studies (Campbell & Wesley, 1993). Volatility driven by events is problematic for event studies because it may result in mis-specification of test statistics (Corrado, 2011). The standard market model assumes that the variance is constant over time. However, given the increasing variance reported in the empirical studies discussed above, this assumption is not valid.

To illustrate this point, the variance in the ARs estimator (i.e., the prediction error) is estimated using the residual variance obtained from the market model over the estimation window period. However, it is likely that there exists heteroscedasticity or event-induced variance. In this case, the variance in prediction errors would be higher than that in regression disturbance. This is because prediction errors are influenced by both errors in estimation of the parameters and disturbance variance as a result of the reaction of the security return to a random shock from the event announcement (Beaver, 1968; Binder, 1998). In this case, both the residuals and prediction errors derived from the standard market model are not independent across time, which contradicts the underlying assumption that security returns are IID over time.

Brown and Warner (1980, 1985) point out that it is important to consider the impact of increased variance on the accuracy of traditional test statistics, arguing that failure to account for this issue may lead to mis-specification. Likewise, Boehmer et al. (1991) indicate that failure to adequately handle potential factors that contribute to different announcement effects will lead to inappropriate measurement of the dispersion increase on the event day. The power of tests can be enhanced by modelling the volatility process using an appropriate method, as discussed below.

Various models have been proposed by researchers to tackle the problem of increasing variance in daily returns. Collins and Dent (1984) suggest a generalised least squares method that addresses the issue of increasing variance (heteroscedasticity) in ARs for an individual firm during the event period; Froot (1989) proposes a method of moments estimator; and Corrado (1989) develops a nonparametric test to accommodate event-induced variance. Another approach, proposed by Boehmer et al. (1991), is computed by first standardising the returns of the event period based on the variance in residuals from the estimation window and then dividing the cross-sectional mean of the standardised returns over the cross-sectional standard deviation to obtain a test statistic.

Frequently employed time-varying volatility models in the empirical finance literature include the autoregressive conditional heteroscedasticity (ARCH) model developed by Engle (1982) and its extension, the GARCH model proposed by Bollerslev (1986). The utility of GARCH classes of time series models in the measurement and prediction of volatility is established in numerous studies. In the research of Akgiray (1989), various ARCH and GARCH specifications are utilised to examine both the time series characteristics of stock returns and the predictive capabilities of ARCH and GARCH models compared with alternative models such as the exponentially weighted moving average and historic simple average methods. The findings from the empirical analysis of Akgiray (1989) demonstrate that the GARCH model exhibits superior performance in both describing and predicting volatility.

Poon and Granger (2003) provide a comprehensive overview of the literature on volatility forecasting based on an extensive survey of the methodologies and empirical results presented in 93 research papers. They conclude that the ARCH and GARCH classes of time series models are highly valuable in the assessment and prediction of volatility, although GARCH appears to be superior to ARCH. Along similar lines, Savickas (2003) analyses the performance of abnormal returns in the existence of volatility based on four approaches including (1) the traditional (Brown & Warner, 1980), (2) standardised cross-sectional (Boehmer et al., 1991), (3) mean rank (Corrado, 1989) and (4) GARCH-based approaches. The analysis encompasses both the event and non-event periods and considers the influence of increased variance caused by events. Savickas tests a GARCH (1,1) model and finds that use of the GARCH approach explicitly captures the volatility process and the event-induced variance increases, providing superior test power.

Corhay and Rad (1996) empirically demonstrate lack of efficiency of the least square estimator in the presence of ARCH effects. They test ARCH effects in the residuals of the market model using the Lagrange multiplier (LM) approach of Engle (1982) and find strong evidence of ARCH features. The authors resolve this problem by adjusting the market model for the GARCH process, which assumes that the residuals can be conditionally heteroscedastic. Table 1 in Corhay and Rad (1996, p. 534) compares results for ARs and CARs between the market model and the market model adjusted for GARCH; the authors attribute differences to the fact that the parameter estimator for α and β based on the market model is less efficient than the estimator for the regression parameters adjusted for GARCH effects.

Olmo et al. (2011) contend that even in periods of fluctuating market volatility, the GARCH (1,1) model makes it possible to detect cases of possible insider trading that likely drive the price movements causing ARs. In a review of event studies based on volatility of returns and trading volumes, Yadav (1992) points out that GARCH forecasts outperform alternative forecast time series models including those based on historical volatility, which is demonstrated by their growing use compared with alternative forecasts.

Having examined how studies generally deal with the effects of increasing variance, the discussion now turns to the problems of thin trading and serial correlation, which may affect the process of modelling ARs. A thinly traded security refers to shares that are infrequently traded. The Tadawul is categorised as an emerging stock market in which thin trading is a common occurrence (Abraham et al., 2002; Harrison & Moore, 2012; Nikkinen et al., 2020).

Evidence from over four decades shows that with nonsynchronous trading of securities, the OLS estimators of the market model parameters are inconsistent and biased when based on daily data (Scholes & Williams, 1977). These findings are in line with evidence reported by Dimson (1979) that the β estimates from the market model are seriously biased when stocks are traded relatively infrequently; thus, the impact of this issue on the coefficient of the market model should be carefully handled. Several approaches are proposed in the literature to tackle these issues, including the Scholes–Williams approach, GARCH (1,1) and ADL (1,1) (i.e., first-order autoregressive [AR] process).

The approach proposed by Scholes and Williams (1977) is commonly used to mitigate the impact of thin trading effects and to obtain unbiased and consistent parameter estimates for daily returns data (Corhay & Rad, 1996; Lagasio & Brogi, 2021). This approach employs a consistent estimator for the parameter β accounting for nontrading effects under the assumption that the underlying return process is uncorrelated over time. Although Scholes and Williams (1977) provide empirical evidence that the nontrading adjusted β estimates of thinly traded securities are around 10–20% higher than the unadjusted estimates, Dimson (1979) reviews a number of approaches dealing with biases in estimates of β that result from thinly traded shares and suggests that the Scholes–Williams approach is not affected by nontrading bias. However, it exhibits a significant level of inefficiency.

In his examination of the performance of market model prediction errors for a large number of daily Center for Research in Security Prices (CRSP) returns, Jain (1986) uses the market model taking into account the impact of thin trading on the distribution of the ARs using the β estimate of the market model and adjusts the model using the Scholes–Williams approach. He compares the distribution of the ARs after making an adjustment to their counterparts estimated from the usual OLS β. Jain observes that correction based on the approach of Scholes–Williams does not improve the distribution based on the OLS method, and any differences are negligible. Thus, MacKinlay (1997) argues that adjustments for thin trading are generally not significant. Miller et al. (1994) suggest fitting an AR (1) model to account for the presence of autocorrelation caused by infrequent trading. Lo and MacKinlay (1990) indicate that all nontrading probabilities can be estimated using the first-order autocorrelation.

With respect to issues of both high volatility and serial correlation in the context of an emerging market, in particular the Tadawul, Suliman (2012) employs five GARCH family models—including GARCH (1,1)—to model and estimate daily stock returns volatility in the Tadawul for the years 2007–11. The researcher first estimates the residuals based on OLS regression to verify the presence of heteroscedasticity in the residuals, using Engle's LM test. Based on the five types of GARCH model used by the author, the findings suggest that the daily returns data exhibit significant departure from a normal distribution and show the presence of heteroscedasticity in the residuals. With a particular focus on the GARCH (1,1) model, Suliman (2012, table 5) reports estimation results showing that the parameter estimates of the GARCH (1,1), α and β, demonstrate that the conditional volatility of stock returns exhibits a significant degree of persistence at the 1% confidence level.

Like Suliman (2012), Mhmoud and Dawalbait (2015) conclude that the daily returns of the Tadawul depart from normality and suffer from heteroscedasticity. The authors analyse the performance of several GARCH models to estimate volatility in the Tadawul and point out that the parameter estimate for the GARCH (1,1) is close to unity, showing a strong level of persistence in the conditional volatility of stock returns of the Tadawul. Harrison and Moore (2012) and Abdmoulah (2010) examine the efficiency of some stock markets in the MENA region, including Tadawul. Both studies use a GARCH model considering the effects of thin trading, and their findings are largely similar, showing that use of the model has notable benefits by reducing bias. Abdumoulah (2010) advocates for use of GARCH family models and suggests that the specification of this type of model exhibits a superior fit to empirical data on returns and is capable of overcoming the issue of thin trading.

The assessment of ARs is heavily reliant on the task of modelling ARs; thus, careful modelling is very important for the successful application of the market model. If the residuals are heteroscedastic (the variance changes over time) or serially correlated, the residuals will not be IID. Akgiray (1989) states that a plausible return-generating process for stock returns is an AR process of first order (AR-1) with conditional heteroscedastic innovations; specifically, GARCH (1,1) processes show a highly satisfactory fit with the data. With respect to changing variance, Engle (2001) indicates that the coefficients for an OLS regression are unbiased, but ‘the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision’. Brown and Warner (1985) suggest that the power of tests can be enhanced by appropriately incorporating the volatility process into the model.

To obtain efficient parameter estimates and consistent test statistics, certain assumptions must be satisfied. Use of the standard market model is restricted because it assumes that the data are homoscedastic and not serially correlated. Therefore, Engle’s LM test is computed in the current study to check whether the residuals predicted by the conventional OLS are heteroscedastic. If the LM test suggests that the data suffer from conditional heteroscedasticity, the GARCH (1,1) process will be considered, suggesting that the variance in errors on a certain day is not a constant but differs depending on the magnitude of the error term and its variance on the preceding day.

Unlike the simple market model, the upgraded version of the market model not only computes single-day ARs, but also considers their variance using the returns of a subset of data from the estimation window period. Thus, to better estimate the AR and obtain more realistic estimate variances, the regression market model is extended, with the underlying assumption that the daily variance in estimation errors is not constant over time; however, it is generated through a GARCH (1,1) process.

Monterio et al. (2007) note that use of the GARCH approach alone runs the risk of overestimating ARs if the returns on a firm's stock on one day tend to be serially correlated with the returns on that stock on days that are close by. To control for the existence of serial correlation and thin trading in estimation errors in returns data for securities, the statistical relationship between the return of a stock and the return of the market portfolio is calculated using a market model that includes the lagged values of both stock and market returns. The method of inclusion takes the form of proxying the error in the prior day and thus reduces the impact it may have on the contemporaneous stock return.

To improve the performance of an OLS and obtain more reliable estimation, the ADL (1,1) model is used; this extended version of the market model maintains its desirable properties in this set-up. This means that the model predictors include a lagged version of both dependent and independent variables. To verify whether the residuals predicted by conventional OLS estimates are correlated, the first procedure is carried out on the assumption that the residuals are not serially correlated. The Durban–Watson test is implemented by calculating the Wald statistic for the parameters of the lagged residuals in an auxiliary OLS regression, as proposed by Brooks (2019). Overall, based on the review of the relevant literature discussed so far, which demonstrates the importance of consider the effects of heteroscedasticity and serial correlation on the process when modelling ARs, the present study considers the potential impacts of such issues. This leads to development of two sub-hypotheses, proposed here in null form:

H_{05a}: The daily variance in estimation errors of the market model is constant over time.

H_{05b}: The error terms of the OLS market model are not serially correlated.

4.3.5 Investigating Sample-specific Effects

The previous section considers a variety of aspects that may affect the process of modelling ARs and AVs. That section also sheds light on other factors that may have an impact, particularly on the MCMs. As explained earlier, several studies use this approach as an indicator of the level of possible insider trading activities by assessing the statistical significance of stock price and volume movements surrounding the days of SAs. However, ensuring the independence of the MCMs in relation to other factors is important.

Dubow and Monteiro (2006), who developed the established MCM, consider potential sample-specific effects by examining six factors that may influence the measure: firm size; stock volatility; stock liquidity; firm innovativeness; size of the CARs over the event window; and industry dummy variables. They document that there is unlikely to be a major identification problem; however, a more sophisticated method that takes account of the effects of these factors is needed. Therefore, minor adjustments are later incorporated by Monteiro et al. (2007) who employ econometric analysis to examine the extent to which changes in the MCMs might be explained by other variables.

The present study examines the factors considered in the above studies with the exception of firm innovativeness, because data on this factor are not available for companies listed in the Tadawul. Further, the study builds on the literature by adding two factors, information asymmetry and trading activity, to investigate whether changes in any of the seven factors affect the MCMs. Proxies for these factors, along with the model used are discussed in Section 5.6.

A considerable body of market microstructure literature pioneered by Kyle (1985) and Glosten and Milgrom (1985) and including the extended work of Collin-Dufresne and Fos (2015) and Ahern (2020), analyses trades with liquidity and asymmetric information, as measured by a range of metrics, indicating an increase in information asymmetry among market participants. Information asymmetry can lead some investors to differ from the average price and thus create distinct trade motivations, creating a strong positive volume–volatility relationship (Karpoff, 1987). Wu (2019) finds that changes in information asymmetry strongly define insider ARs.

Kothari and Warner (2007) recommend the application of discrete choice models, such as probit or logit models, to examine the relationship between the occurrence of an event and firm-specific characteristics. The authors comment that such methods serve as a valuable addition and complement conventional event study method. Erdugan et al. (2019) indicate that the logit regression can efficiently estimate the likelihood correlated with a positive return in asset returns. In the context of the event study MCMs, Monteiro et al. (2007) and Goldman et al. (2014) utilise logistic regression models to investigate whether changes in the MCMs are driven by changes in the six factors mentioned above that cause potential sample-specific effects. Following these studies, the present study considers the use of logistic regression to investigate whether changes in these factors may influence the MCMs. Thus, the null hypothesis to be examined is that:

> H_{06}: The MCMs of the return event study are not significantly influenced by the sample-specific characteristics including firm size, liquidity, volatility, information asymmetry, trading activity and absolute CARs.

4.3.6 Trading Volume Event Study Approach

The preceding sections present a methodological review that specifically concentrates on the returns event study approach and the process of modelling ARs, computing CARs and other aspects relevant to a returns analysis. In addition to a returns-based event study, the present study performs a volume-based event study. The impact of insider trading activity extends beyond price movements; it also influences trading volumes (Engelberg et al., 2018). In the market microstructure literature, high trading volumes are associated with the release and arrival of new information (Copeland, 1976; Kyle, 1985). Academics, experts and securities regulatory agencies consider that unusually high trading volumes in advance of corporate events are often an indicator of the presence of insider trading activity (Augustin et al., 2019; Bhattacharya et al., 2000; Meulbroek, 1992; Mohil et al., 2020; Monteiro et al., 2007; Prevoo & ter Weel, 2010; Wong, 2002).

The volume event study approach is conducted in a similar manner to returns event study as discussed in Section 4.3.1, but with some differences. The first involves using daily trading volumes rather than daily price data to conduct the event study. This means that the analysis is carried out to examine the extent to which APAVs are detected prior to SAs. The second difference concerns the construction of a trading volume measure with based on the characteristics of raw trading data. These two aspects are explained in more detail in Section 4.3.6.1 and 4.3.6.2, respectively. The third difference is in the approach to modelling of expected trading volumes, as discussed in Section 4.3.6.3. The following sections provide a comprehensive discussion of key elements associated with each of these modifications.

4.3.6.1 Measures of Abnormal Trading Volumes

Having provided a brief explanation of the volume event study approach, this section discusses the first way in which it differs from the returns event study approach. The literature presents a range of trading volume measures; for example, shares traded, number of trades, dollar volume, share turnover ratio, dollar turnover ratio and percentage of outstanding shares traded. The most used volume metrics in trading volume event study settings are (i) the daily dollar value of shares traded, (ii) the fraction of outstanding shares traded, and (iii) the daily number of common shares traded (Ajinkya & Jain, 1989; Beaver, 1968; Bhattacharya et al., 2000; Chae, 2005; Cready & Ramanan, 1991; Meulbroek, 1992; Monteiro et al., 2007; Prevoo & ter Weel, 2010).

Bhattacharya et al. (2000) examine corporate news announcements on the Mexican Stock Exchange and measure trading volume in two ways. First, the daily trading volume of individual stock for a certain day is divided by the average daily trading volume for that stock in the event period to produce a normalised measure that is not dependent on firm size. Second, the normalised volume per share is averaged over all shares for every day over a 91-day event period (–80 to +10). Beaver (1968) uses a weekly average of the daily percentage of shares traded where the weekly volume is divided by the number of shares outstanding, and the ratio of weekly shares traded is divided by the number of trading days.

In their empirical study of the properties of daily trading volume using samples of NASDAQ and NYSE securities to observe abnormal trading volume, Campbell and Wasley (1996) examine metrics that include the number of shares traded as well as the percentage of outstanding shares traded. The authors find that the latter presents a significant degree of skewness, even after log transformation, and the former increases monotonically with firm size. Antweiler and Frank (2004) use two measures of trading volume that include the log number of traded shares. Among the several volume measures discussed earlier (in the introductory of the current section, Lo and Wang (2000) employ the turnover ratio using the total number of shares traded and find that the total dollar volume normalised by the market value gives the same results.

Volume metrics would be more functional if they considered the manner in which investors engage in trading. In regard to the Tadawul, Alzahrani et al. (2013) examines causal factors in the price impact of block trades (defined as any trade with over 10,000 shares), revealing that a common behaviour among informed traders in the Tadawul is trading a large volume with the aim of increasing block purchases. Other studies on trading volumes in the Saudi context use daily data on the number of shares traded (Alhussayen, 2022; Alsabban & Alarfaj, 2020). Thus, the daily number of common shares traded may be appropriate.

Importantly, in addition to considering underlying drivers of trading activities, selection of a suitable metric for measuring volume is closely linked to the specific model used to estimate AVs. In the context of the volume event study MCMs, Monteiro et al. (2007) use the daily number of shares traded. Further, the characteristics of the daily number of shares traded metric are established by the seminal study of Ajinkya and Jain (1989), in conjunction with expectation models of abnormal trading volumes employed in the current study. Therefore, the volume measure selected in the current study is the daily number of shares traded.

4.3.6.2 Characteristics of Trading Volume Data (Non-normality)

Having provided a rationale for the chosen volume measure, it is important to illuminate a crucial aspect pertaining to characteristics of trading volume data prior to delving into a discussion of expectation models. Empirical evidence from over three decades shows that raw trading volume data possesses undesirable statistical properties including a distinct departure from a normal distribution (Ajinkya & Jain, 1989; Cready & Ramanan, 1991; Yadav, 1992). The most common approach used to handle non-normality is the natural logarithm function.

Ajinkya and Jain (1989) empirically investigate the properties of the daily trading volume of common stocks traded on the NYSE and find that prediction errors for the untransformed volume measures examined in their analysis are significantly positively skewed, with thin left tails and fat right tails. Likewise, Cready and Ramanan (1991) support the findings of Ajinkya and Jain (1989) showing that without transformation, the median, skewness and kurtosis for the whole sample exhibit positive skewness and significant departures from normality. Nevertheless, natural log transformed volume data are approximately normally distributed (Yadav, 1992).

Log transformation of the volume measure is used in many studies (e.g., Ajinkya & Jain, 1989; Alhussayen, 2022; Chae, 2005; Cready & Ramanan, 1991; Monteiro et al., 2007; Wu, 2019). The method of inducing abnormal trading employed by Ajinkya and Jain (1989) is conducted by adding the percentage of the mean estimation (non-event) period volume to the volume of event date and then log transforming the sum.[28] Campbell and Wasley (1996, table 1) present untransformed volume date for the number of shares traded metric, with average skewness and kurtosis coefficients of 3.3 and 17.0, respectively. After natural log transformation is applied, the skewness declines to –0.51 and kurtosis to 3.1. Similarly, Chae (2005) demonstrates that once the log function is applied, extreme skewness and kurtosis demonstrating a clear break from normality decline from 8.596 to –0.098 and from 159.439 to 0.701, respectively.

The empirical evidence discussed so far clearly shows the significance of employing log transformation, which represents a substantial refinement resulting in volume measures that are nearly normally distributed. Accordingly, the present study considers using log transformation of raw trading volume data as this common practice yields an acceptably high degree of normality. This is also in line with previous studies (Ajinkya & Jain, 1989; Alhussayen, 2022; Chae, 2005; Cready & Ramanan, 1991; Monteiro et al., 2007; Wu, 2019).

4.3.6.3 Models for Estimating Abnormal Trading Volumes

Having discussed trading volume metrics and the properties of trading volume data, the focus of the discussion now shifts towards the expectation model for abnormal trading volumes. There is a variety of expectation models for trading volume and the difficulty for trading volume event studies is that there is no generally accepted economic model for generating ex ante volume expectations, like there is for returns (Yadav, 1992).

[28] The following form is the log transformation of the adjusted volume in Ajinkya and Jain (1989): $log\ (1 + \$VOLUME_e + p * M\$VOLUME)/log(l + MKT\$VOLUME_e)$, where $\$VOLUME_e$ is the value of trading in thousands of dollars on the event date e, *M$VOLUME* is the mean of dollar volume over the non-event estimation period, $MKT\$VOLUME_e$ is the value of outstanding shares on the event date e, *p* is the inducement percentage of abnormal trading.

Regarding expectation models for identify abnormal trading volumes, there are several statistical approaches. For instance, Bamber (1986) employs a median-adjusted approach by using the median trading volume of each firm for the calendar year. The median percentage of shares traded and standardised residuals are taken as point estimates of the trading volume for each period. To determine whether the number of observations exceeded the median trading level, Bamber performs a binomial test and finds abnormal trading volumes were high over the event period for days –7 to +7.

Ajinkya and Jain (1989) and Cready and Ramanan (1991) compare the results from three expectation models: the mean-adjusted trading model; the market model of trading volume; and the market model of trading volume with adjustment to first-order serial correlation using estimated the generalised least squares (EGLS) procedure to account for autocorrelation in the residuals. Ajinkya and Jain (1989) demonstrate that the trading volume market model is more powerful than the mean-adjusted model for detecting abnormal trading on a given day. This expectation model is based on a volume market model regression line using OLS estimation.

Cready and Ramanan (1991) also document that the market model marginally outperforms the mean-adjusted model. Further, Brown and Warner (1985) point out that the mean-adjusted model is sensitive to clustering of event dates. Likewise, Yadiv (1991) notes that this model is significantly less powerful under event clustering. The market-adjusted volume ratios approach is used by Harris and Gurel (1986), but this model is no different from a market-adjusted model as it ‘assumes that ex ante expected returns are equal across securities, but not necessarily constant for a given security’ (Brown & Warner 1980, p. 208).

Having considered several models and shown the superiority of the trading volume market model, this study utilises the trading volume market model to estimate expected trading volume. The model is estimated over the daily shares trading of the security and market index across the estimation window to obtain the expected volume. When the expected trading volume is estimated, the AVs for every firm can be identified as the difference between the expected volume and the actual volume. Then, the CAVs are calculated by aggregating the AVs across the pre- and post-event window under investigation. To evaluate the statistical significance of the distribution of the CAVs during the event window being examined, the bootstrap test statistics and quantile thresholds are calculated, as described in Section 5.4.3.

After identifying statistically significant events that meet the specified threshold, the volume-based market cleanliness measures (VMCMs) is calculated as the proportion of SAs that were preceded by APAVs. SAs refers to statistically significant CAVs during the post-event window that suggest the announcement contains important news and should be regarded as a SA. Conversely, APAVs are statistically significant CAVs over the pre-event window that can be viewed as indicators of the occurrence of potential insider trading activities. Therefore, the null hypothesis to be tested is that:

H_{07}: The announcement had no significant impact on the distribution of CAVs over the post-event window.

Subsequently, if the tested event is a statistically SA, the assessment proceeds to examine if APAVs have not occurred prior to the SA, which requires the absence of significant CAVs across the pre-event window as proposed in the following null hypothesis:

H_{08}: The announcement had no significant impact on the distribution of CAVs over the pre-event window.

4.3.6.4 Modelling Trading Volume in the Presence of Volatility and Serial Correlation

The previous section reviews the market model of trading volumes without considering the presence of volatility and serial correlation. Studies raise concerns about the validity of the model when volatility and autocorrelation are present in volume data. An empirical problem emerges in the seminal work of Lamoureux and Lastrapes (1990), who find a relationship between trading volume and heteroscedasticity in the form of volatility clustering. In their studies, Liu et al. (2021) and Do et al. (2014) provide empirical evidence of a strong positive relationship between volume and volatility. Further, information asymmetry can lead some investors to differ from the average price and thus create distinct trade motivations that cause strong positive volume volatility (Karpoff, 1987). Among various theoretical models that underpin the relationship between volume and volatility are the mixture of distributions hypothesis (MDH) proposed by Clark (1973), the sequential information arrival hypothesis (SIAH) introduced by Copeland (1976) and the asymmetric information model developed by Kyle (1985).

The MDH assumes that daily price movements are influenced by a series of information flows and the occurrence of unforeseen news is accompanied by trading activity that is higher than usual. The changes in price are a mixture of distributions with volumes as the mixing variable (Epps & Epps, 1976). The MDH suggests that trading volumes are responsive to a variety of incentives such as the amount at which new information enters the market and the different opinions held by market participants regarding the impact of the released information.

Yadav (1992) indicates that the conditional variance in the process of price formation for a single transaction implies stochastic dependence between volume transactions and the change in price from one transaction to another. The author states that under the MDH, the volume of a transaction affects the price change variance, so volume and volatility are also correlated at the transaction level. The MDH proposes a significant and positive correlation between volatility and volume (Liu et al., 2021). Carroll and Kearney (2012) point out that when there is a large degree of intermittence in volatility and the volume process stays consistently smooth, the structures of the two series are sufficiently different to suggest they are not driven by the same underlying mechanism. The authors suggest that in these instances, the MDH does not apply.

The SIAH introduced by Copland (1976) assumes that a piece of information arrives during the trading period to only one trader, who trades on this information before it is disseminated to other traders. A trader who sees information as negative is a pessimistic trader while a trader who considers it positive is an optimistic trader. Copland defines the trading period according to operational time not calendar time, and considers that volume and price changes are reactions to new information during each trading interval. Once all traders acquire relevant information, the total volume depends on the sequence of both optimists and pessimists through which final equilibrium is reached. Yadav (1992) points out that simulation evidence documents a positive relationship between volatility and volume.

Under the asymmetric information model, Kyle (1985) distinguishes three types of trader: informed traders who have superior knowledge and trade on private information to profit; investors who trade randomly, referred to as uninformed noise traders; and ;market makers who have no private information but learn continuously from volume and price changes to effectively establish market prices. Kyle shows that noise trading causes confusion for market makers, allowing insiders to profit at the expense of noise traders because the market maker cannot recognise the two types of traders. Yadav (1992) comments that the variance in this model exhibits a correlation with trading volume; thus, the trades of informed traders and specialist market makers will be clustered, which causes variance to be higher during active trading.

Lamoureux and Lastrapes (1990) incorporate contemporaneous trading volumes into the variance of a GARCH (1,1) model. Their findings indicate that the lagged residuals are no longer significant. The authors contend that the well-demonstrated ARCH/GARCH effects observed in volatility can be attributed to the occurrence of clustering in trading volumes. Liu et al. (2021) assesses the performance of generalised autoregressive conditional heteroscedasticity mixed-data sampling (GARCH-MIDAS); traditional GARCH; and intraday GARCH models with monthly, daily and intraday data for predicting volatility in the China stock market. Based on their empirical findings and the results of a robustness test, the authors conclude that there is a positive correlation between trading volume and volatility, and the GARCH-MIDAS does not exhibit superior performance compared to the traditional GARCH when both are estimated using the same predictors sampled at different frequencies.

In the context of an emerging market, Chuang et al. (2012) study the relationship between trading volume and stock returns, as well as the causal relationship between trading volume and return volatility in 10 Asian stock markets. The authors suggest that the estimation of GARCH models indicates that volatility in trading volume is more persistent in emerging countries than in developed ones. Sabiruzzaman et al. (2010) examine volatility of daily trading volume in the Hong Kong Stock Exchange using both the GARCH and threshold GARCH specifications and find that both models demonstrate good fit with the data. Other studies use the GARCH specification and establish its performance for ARs and AVs; therefore, the present study used the GARCH model to handle the effects the volatility.

With respect to serial correlation, Ajinkya and Jain (1989) examine the presence of autocorrelation and demonstrate that the residuals are significantly autocorrelated. The authors adjust the trading volume market model using EGLS to account for the autocorrelation by incorporating an AR (1) residual autocorrelation structure. They indicate that the EGLS model takes autocorrelation into account. Based on the literature survey detailed above, which provides clear evidence of the effect of high volatility and serial correlation, the present study takes into consideration the possible impact of these issues when modelling AVs.

The preceding section outlines the justification for the present study using the trading volume market, on the basis that it is widely used in trading volume event studies to estimate abnormal trading volumes (e.g., Ajinkya & Jain, 1989; Chae, 2005; Monteiro et all., 2007; Morse, 1981; Prevoo, 2010). However, given the problems of volatility and autocorrelation, the trading volume market model is employed with adjustments to account for volatility clustering by using the GARCH(1,1) model to handle the effects of heteroscedasticity. Further, the ADL model (1,1) is employed to correct for serial correlation. Thus, the null sub-hypotheses to be tested are as follows:

H_{07a}: The daily variance in the estimation errors of the trading volume market model is constant over time.

H_{07b}: The error term of the OLS trading volume market model is not serially correlated.

4.3.7 Relationship Between Stock Return and Trading Volume

Preceding sections provide an extensive review of return and volume event studies. Investigation of the relationship between the stock return and trading is rare the Tadawul, particularly in the context of market cleanliness methodologies. Thus, one objective of the present research is to examine the relationship between the return and volume event study of the market cleanliness study. Numerous academic research has examined the correlation between the stock return and trading volume, with conflicting findings.

Smirlock and Starks (1988) empirically examine the relationship between absolute stock price changes and trading volume using a sample from the NYSE. Their findings reveal that a significant relationship at the firm level that exhibits greater strength around earnings announcement periods. A study by De Medeiros and Doornik (2006) on the Brazilian equity market finds evidence of both a simultaneous and dynamic correlation between stock returns and trading volume, implying that prediction of either one of these variables is only marginally enhanced by understanding the other. In the same vein, Chandrapala (2011) uses a sample of all listed stocks in the Colombo Stock Exchange and finds a positive relationship between stock returns and contemporaneous changes in trading volume. Gul and Javed (2009) discover significant positive correlations between different measures of trading volume and the behaviour of the Karachi Stock Exchange index.

Chung (2012) examines the contemporaneous and causal relationship between trading volume and stock returns using the daily price and daily trading volume across 10 Asian stock markets.[29] The author presents empirical evidence for a contemporaneous relationship between the volume of the trading stock and the returns, as well as a causal relationship between stock returns and trading volume; both are significant and robust over all stock markets included in their sample. Similarly, Naik et al. (2018) study the impact of trading volume on return volatility in a South African stock exchange and observe a positive and statistically significant relationship between contemporaneous trading volume and stock return volatility.

Akpansung and Gidigbi (2015) identify a long-run relationship between change in stock returns and trading, but the direction of the relationship is not confirmed. Remorov (2014) provides empirical evidence of a negative proportional relationship between trading volume and the square of the stock price. In the context of the Tadawul, it was discovered that trading volume does not possess the ability to transmit information to prices and does not affect price movement, as shown by Alhussayen (2022).

Monterio et al. (2007) use a MCMs to investigate the relationship between abnormal price and volume movements. In their analysis of a sample of takeovers, 43% of announcements that experienced APPMs also exhibited APAVs before the SA day. If an announcement has an impact on stock returns, this should be reflected in trading volumes. In

[29] The ten Asian stock markets included in the sample of Chuang's et al. (2012) study consists of Hong Kong, Japan, Korea, Singapore, Taiwan, China, Indonesia, Malaysia, the Philippines, and Thailand over the period from 1 January 1998 to 31 December 2007.

this case, there should be a relationship between a change in trading volume and stock return movements. Therefore, the null hypothesis to be examined is as follows:

H_{09}: There is no significant relationship between the MCMs for return and volume analyses where SAs that were accompanied by APPMs were not also accompanied by APAVs and vice versa.

4.4 Chapter Summary

This chapter reviews studies of prominent scholars in securities law and financial markets that strongly emphasise the importance of securities laws and their pivotal rules for the integrity and development of the capital market. The chapter also reviews studies by academics denouncing the necessity of high-quality laws and strong legislation alongside strict implementation of these laws. The review covers various metrics and approaches utilised in studies estimating insider trading. The chapter provides a thorough methodological survey of empirical events studies conducted by researchers to investigate and quantify abnormal movements in stock returns as well as trading volumes, considered likely to be caused by insider trading activities. A review of previous studies that examines several factors that may have impact the market cleanliness methodology as well as the relationship between the return and trading volumes is presented. The next chapter describes the research methodology and methods used to test the research hypotheses formulated in this chapter.

Chapter 5: Research Design and Implementation

5.1 Introduction

This chapter describes the data sample and provides a detailed description of the methodologies and methods employed in this research to test the research hypotheses developed in the previous chapter. The empirical approach conducted in this study as well as the appropriateness of the use of statistical models to compute the model parameters is demonstrated in detail in this chapter. Before diving into the methodology, it is better to reiterate details of the research topic. As explained in Chapter 1, this thesis seeks to investigate the impact of financial reforms on the integrity of the Tadawul with a particular focus on potential insider trading activities and information leakage, by measuring the market cleanliness level of the Tadawul over the relevant period. The study employs the methodologies of the event study market cleanliness measures with minor adjustments for Tadawul data.

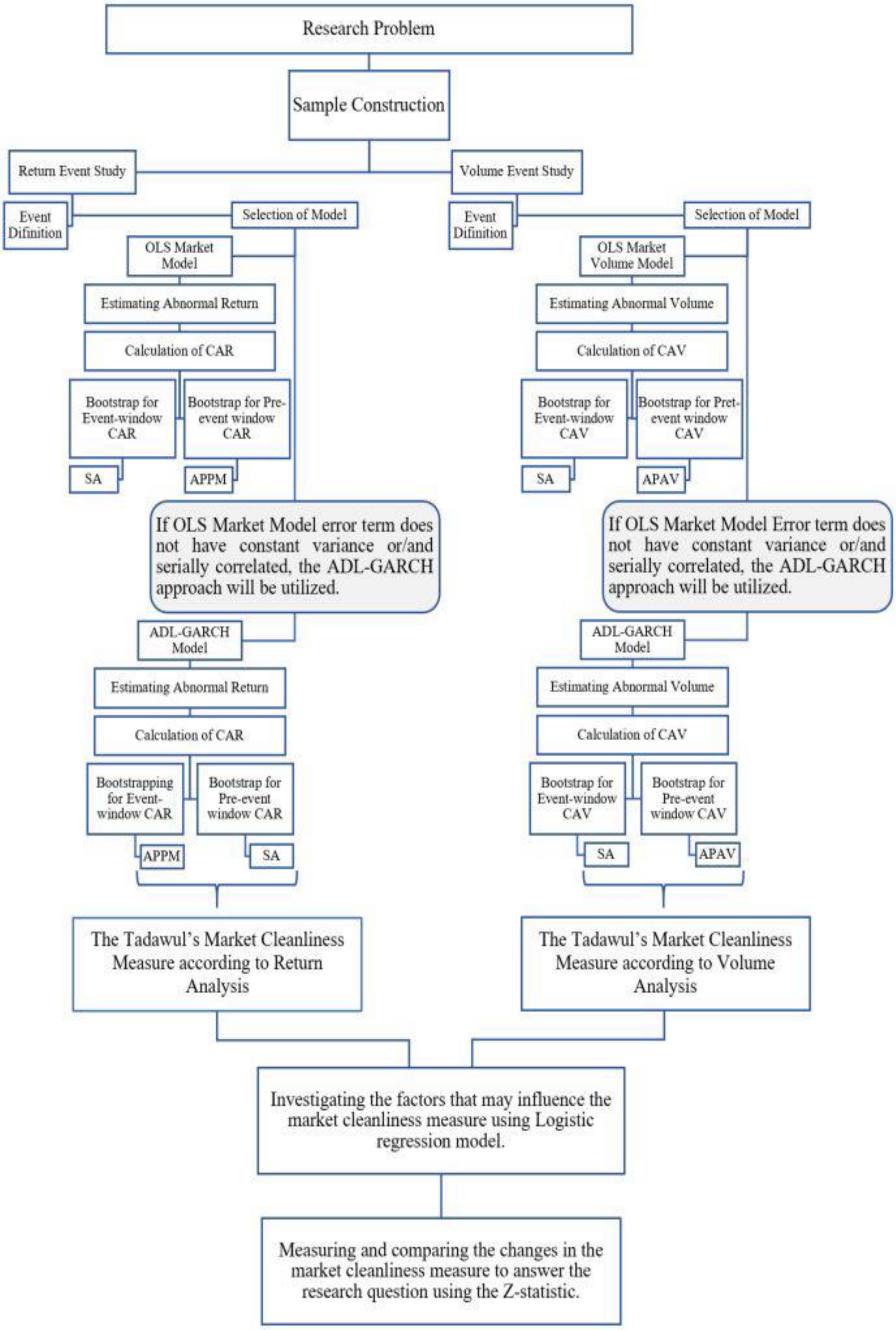
A returns event study analysis is carried out to examine the existence of APPMs ahead of SAs with a focus on the daily stock price movements. The returns analysis employs two approaches and a variety of econometrics models that include the SLR, GARCH (1,1), ADL (1,1) and ADL-GARCH for modelling ARs to better capture the relevant features of the data and derive meaningful conclusions. This chapter addresses factors that may influence the measure of market cleanliness using a logistic regression model to ensure that the measure is not affected by these factors, allowing for more meaningful conclusions.

Similarly, the trading volume event study seeks evidence of APAVs in advance of SAs with a focus on the daily number of shares traded. The trading volume analysis uses several statistical models to model abnormal trading volumes. In light of the review addressed in Chapter 4, the volumes analysis considers four main aspects: (i) the trading volume metrics, (ii) the volume data characteristics, (iii) the day-of-the-week effect in stock market volume and (iv) mapping four scenarios to cope with autocorrelation and high volatility. Taking these aspects into consideration necessitates the use of complex models to obtain a reliable estimate of the AVs.

The remainder of this chapter is organised as follows. Section 5.2 describes the data sample, and it is divided into four subsections that outline the sample period, the data source as well as selection criteria and type of historical data frequency. Section 5.3 introduces the event study analysis performed in this study. As explained earlier, this thesis encompasses four empirical methods aimed at investigating the research questions and testing their respective hypotheses. The first approach, labelled ‘conventional market cleanliness measure according to the MM’ approach, is outlined in Section 5.4. For the remainder of the thesis, the acronym MM is used to refer to this approach. Section 5.5 describes the second approach labelled ‘advanced market cleanliness measure according to ADL-GARCH approach’. Henceforth, the abbreviation ADL-GARCH is used to refer to this approach. The third empirical work pertains to the analysis of the potential effects of the sample characteristic factors addressed in Section 5.6. The fourth analysis, described in Section 5.7, is concerned with the trading volume event study. Section 5.8 summarises the chapter. Figure 5.1 presents the conceptual framework of the analysis carried out in this study.

Figure 5.1

The Conceptual Framework of the Analyses Conducted to Test the Research Hypotheses and Answer the RQs.



5.2 The Data Sample

The methods employed in this study use publicly available data from the Tadawul for the period 2011–2020. The data are described in terms of their source, period, format, characteristics and the selection criteria that implicate restrictions imposed by data availability for the purpose of conducting a more reliable analysis. The study also uses secondary data consisting of firms' public announcements, daily stock prices and daily trading volumes over the relevant period covering all firms across various sectors on the Tadawul. The econometrics models employed in this study are constructed using time series data for particular variables and high-frequency data in the daily form, for the reasons outlined in Section 5.2.4.

5.2.1 Sample Period

The sample period spans over 10 years from 2011 to 2020 (the relevant period). The selection of this period is in line with the study aims in which that the Tadawul witnessed a raft of reforms and transformation during this decade. For example, this period was accompanied by several substantial developments, including the relaxing of ownership limits for foreign investors in 2015,[30] obligating publicly traded companies to adopt the International Financial Reporting Standards (IFRS) in 2016[31] and financial reforms launched in 2016, ending with inclusion of the Tadawul in major global financial indices during 2018–2020.[32] [33]

Thus, the scope of the study extends over two main periods relating to introduction of the financial reforms. The first period covers a pre-reform period from 26 April 2011 to 25 April 2016. The second period encompasses a post-reform period from 26 April 2016 to 25

[30] https://cma.org.sa/en/Market/QFI/Pages/default.aspx
[31] https://www.cma.org.sa/en/market/news/pages/cma_n_2107.aspx
[32] https://cma.org.sa/en/MediaCenter/PR/Pages/FTSERussell.aspx
[33] https://www.msci.com/msci-saudi-arabia-indexes

April 2020. The data sample is divided accordingly into two segments covering the two periods to separately assess the MCMs of the Tadawul and then compare the changes in the measures between the two periods. Note that because of the collapse that all international financial markets suffered as a result of the COVID-19 pandemic, the data sample is restricted to the period prior to the pandemic, to avoid including heterogeneous data that may seriously impact the analysis and lead to misleading results. Even with this restriction, the size of sample data for the second period is larger than that for the first period because of steep growth in the number of firms listed in recent times. However, the data sample remains fairly consistent over the relevant period analysed.

5.2.2 Sample Source

All firms listed in the Tadawul are obligated to disclose all information that might impact the company's stock value, in an accurate and timely manner without delay.[34] The event study analysis conducted for this thesis focuses on public announcements disclosed by all firms whose stocks are listed in the Tadawul; thus, firms announcements are used as a proxy for these events. The Tadawul All Share Index (TASI), the prime stock exchange index used in Saudi Arabia and the largest in the MENA region, is a major index for the main equity market. It is comprised of and tracks the performance of all eligible firms listed on the Tadawul. Calculation of the index uses all Tadawul indices weighted by the free float market capitalisation and is calculated based on normal trades. The free float market capitalisation is calculated by multiplying an issuer's number of free floated shares by its closing price.[35]

With respect to firms announcements, the task of data collection is handled with great care in this research by considering a selection criterion, described in Section 5.2.3, to ensure

[34] Article 41 of the registration and listing rules stipulates that the issuer (the company issuing securities) must inform the Authority and the public without delay of any important developments, material events and financial reports that fall within the framework of its activities and whose knowledge is not available to the public and affect its assets and liabilities.
[35] https://www.saudiexchange.sa/wps/wcm/connect/b1abb587-30a2-4aee-9e93-cce83abe27d2/Tadawul+Indices+Methodology+-+EN+2020-05-14.pdf?MOD=AJPERES&CVID=n8iuKAl

that no errors exist in the assembled data. This is because some flaws are observed, such as unmatching data among some sources. Although this procedure made data collection costly in terms of time and effort, it was necessary to avoid inaccurate data that may cause mistakes in inference. Ince and Porter (2006) and Chui et al. (2010), among others, raise concerns about the data errors, coverage and quality of data available from DataStream International (DS). For instance, Chui et al. (2010) find that the quality of stock market data sourced from DS, particularly data for emerging markets, is not as ideal as the quality of the data from the database of Center for Research in Security Prices (CRSP). It could be conjectured that the reason for the poor quality of data in the DS may be due to the original source of the data rather than how the DS records or handles it.

It is more likely that the essential difference between different types of data is their source. Therefore, with the exception of the firms announcements sample, which is taken from the Tadawul, I first carefully check the stock prices and trading volumes sample by comparing observations data drawn from DS against the sample data collected from the Saudi official stock exchange. This comparison unveils some differences in the data. For example, the closing prices for some trading days do not match between these sources. However, it is considered that the database of the Tadawul, being the official stock exchange of the KSA is the most accurate source. This database agrees with the quality and truth after further scrutiny procedures with other financial news sources namely Argam[36] and Mubasher.[37]

These news sources are considered a region's leading financial news sources in terms of market data and coverage as they provide real-time updates on financial markets. After further comparison, the data sourced from the Tadawul were found to generally match those from these sources. However, the share prices in the latter are not adjusted for stock splits and dividend distributions. Although security returns could be manually calculated and adjusted

[36] https://www.argaam.com/en
[37] https://global.mubashertrade.com/about-us/

for such corporate actions, the daily adjusted prices are extracted for this study from the Tadawul's E-Reference Data in which the closing prices are adjusted for corporate actions such as splits, spinoffs, rights and dividend distributions.

The Tadawul designed the E-Reference Data[38] system encompasses multiple databases. Among them is the unique Market Data Premium Reports Database (MDPRD), which provides a reliable source of information via a comprehensive historical financial database including the full history of data in the Saudi capital market ranging from corporate announcements, historical adjusted equities prices, financial statements issuers' master data and others. The MDPRD is the most precise and thorough source, providing all information necessary for this research. Therefore, the primary source of the data assembled for this study is the MDPRD.

The data are manually collected from the MDPRD, which is available on the Tadawul website. However, further caution is applied because of imperfections found in some announcements content and dates, which might provoke errors. A filtering process was designed to ensure a unique and clean dataset. Although this source may be the most accurate as it is managed by regulatory body, particularly in terms of announcements contents, dates and times, several points are worth noting.

First, I encountered some minor difficulties with respect to announcement classification because the system does not efficiently retrieve an announcement of interest according to the announcement title entered. The use of keyword filters sometimes leads to retrieval of irrelevant information about wanted announcements, or no results at all despite relevant information being available on the system. For instance, in the Tadawul's bulletin, some of the price-sensitive announcements labelled under the headlines 'Announcements of Material Development' or 'Announcements of the Occurrence of Substantial Event' cannot

[38] https://www.saudiexchange.sa/wps/portal/tadawul/knowledge-center/about/ereference-data?locale=ar

be found despite the existence of information related to these announcements on the relevant companies platforms. The issue of announcement classification seems to arise from how data are input even though issuers are required by the regulatory body to follow identified formulae for the announcement title, type and content. Because of these issues, the dataset is complemented by hand-collected data inspected announcement by announcement for over 45,000 announcements during the relevant period.

In addition to a careful handling of the data collection discussed so far, another cautious was considered which is the changes in trading days that happened during the study period. As the Saudi government switched its official weekend to Friday and Saturday as of 29 June 2013, the present study considers the changes in trading days that happened during the study period.[39] All in all, the sample is collected taking into consideration all aforementioned observations in addition to the selection criteria detailed in the ensuing section, which involves restrictions imposed by the availability of equity data and announcements.

5.2.3 Selection Criteria for Firms Announcements and Equities

The present study requires data on firms announcements and their related securities during the relevant period. The sample of announcements is restricted to unscheduled firms announcements published by issuers during the relevant period. The justification for restricting the selection to unscheduled announcements stems from their merit of being unlikely anticipated, but typically known by corporate insiders. Other types of firms announcements such as dividends or earnings announcements are excluded because they are often prescheduled and usually subject to explicit insider trading embargoes (Cohen et al., 2012). Importantly, one may argue that APPMs found to have occurred prior to scheduled events are not driven by potential insider trading activities, but by the fact that scheduled

[39] https://www.spa.gov.sa/en/bee255bdbb

announcements are predictable. Furthermore, the process of price discovery preceding scheduled events may be attributed to the activities of sophisticated traders, motivated by their acquisition of information and/or the information provided by sell-side analysts (Chen et al., 2020; Weller, 2018). However, APPMs that occurred before unscheduled announcements are more likely to arise from insider trading activities.

The selection is limited to major unscheduled events that fall under the heading 'merger, acquisition, takeover, awarding contract' and two subsets of unscheduled 'good news' and 'bad news' announcements. The data for firms announcements is manually documented to the millisecond. This timing is critical to the analysis because if the announcement occurred outside trading hours, the date of the announcement would be misidentified. The most important task when performing an event study is to precisely define the announcement date. Therefore, great attention is paid in this study to the definition of the event day to ensure that the announcement is made during the trading hours. Indeed, I find that approximately 3% of the announcements sample was published after the close of the market. The collection of firms announcements is conducted by considering not only the date of the announcement but recognising the time at which the announcement was released. If the event was announced after trading hours, the following trading day is designated as the event day (t = 0). The daily stock prices are in the form of adjusted closing prices:

Starting with an initial sample of 2,049 events for all categories of unscheduled announcement covering the entire relevant period and including all firms listed in the Tadawul, the numbers of firms and announcements are reduced to align with the selection sample criteria. The first sample over the pre-reform period (i.e., 26 April 2011–25 April 2016) contains 842 unscheduled announcements; and 1,207 announcements are documented in the post-reform period (i.e., 26 April 2016–25 April 2020). However, filtration and cleaning processes—such as removal of announcements for which the date or time cannot be determined, along with other inconsistent data—are necessary. The study requires clean data related to firms announcements and their related securities prices and volumes for an observation to be included in the sample. Therefore, the following criteria are used to arrive at a clean sample:

1. All firms must have been listed on the Tadawul and published unscheduled announcements during the relevant period.
2. Each announcement must include the firm's daily observations of stock prices and trading volumes, announcement date, time, heading and content.
3. Securities of firms are required to be actively traded during the timeline of the event study (i.e., the entire 261-trading-day period). This means that daily trading data for each stock must be available during the estimation window (which includes the –240 trading days up to –11 days prior to the event day), plus the event day (t = 0) as well as the pre-event window (–10) and post-event window (+10).
4. Stocks that made announcements during the relevant period, including those that were later delisted, and have enough data on daily prices for the estimation window and event window are included.

The final sample analysed for the relevant period consists of 1,958 announcements. Of these, 761 are drawn from 124 companies during the pre-financial reforms period and 1,197 are recorded from 178 firms over the post-financial reforms period. Table 5.1 provides a descriptive overview of the announcements sample and types during the relevant period.

Table 5.1

Overview of the Announcements Sample During the Relevant Period.

Relevant Period	**Year (ended 25 April)**	**No/ year**	**Type of Announcements**					
			Acquisition	Takeover	Awarding contract	Merger	Good news	Bad news
Pre-Financial reforms	2011	106	12	14	22	3	49	6
	2012	145	13	8	40	6	71	7
	2013	144	10	10	40	9	67	8

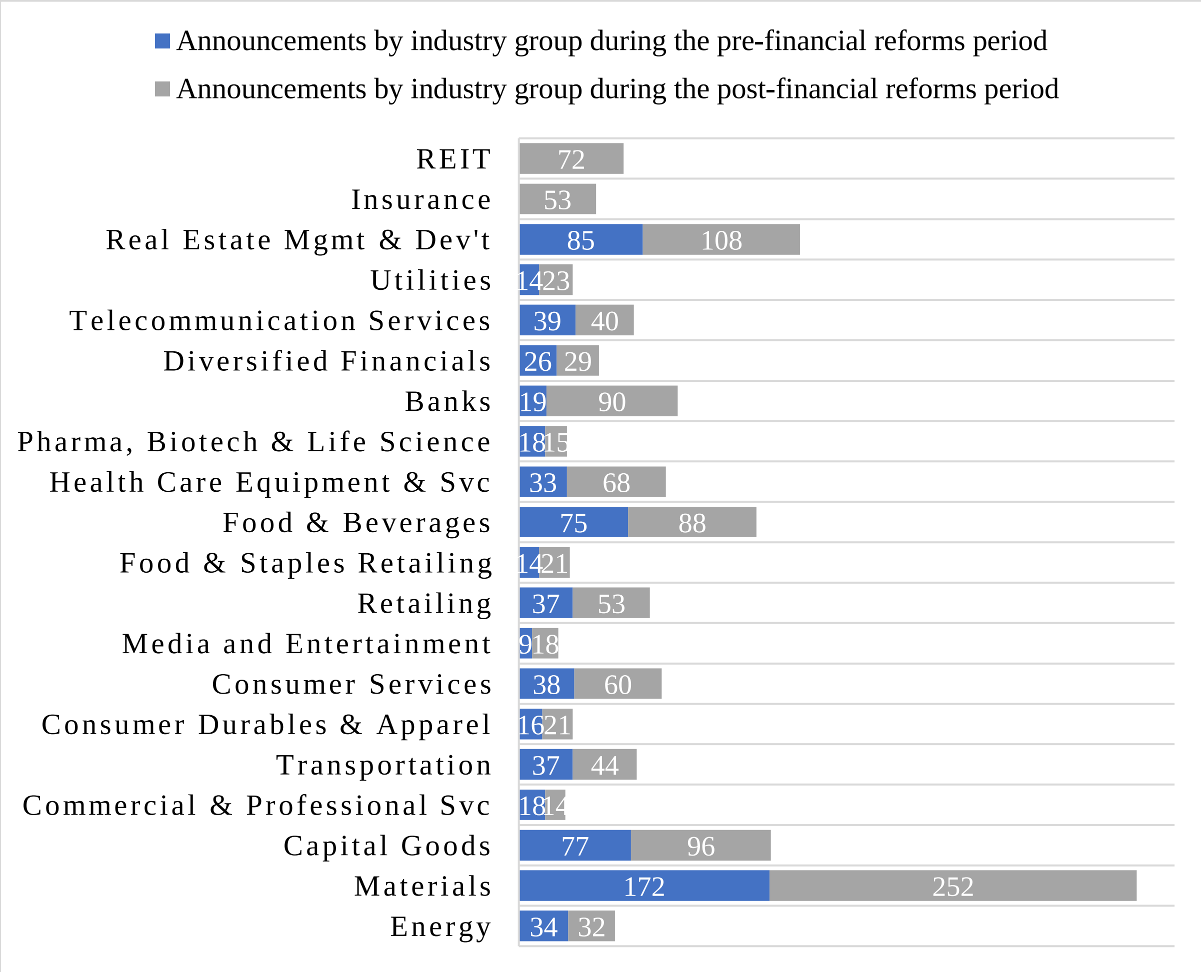
	2014	177	19	15	41	7	82	13
	2015	137	16	15	38	0	62	6
	2016	52	4	5	6	0	35	2
Total	1st half	761	74	67	187	25	366	42
Post-Financial reforms	2016	173	14	11	63	1	77	7
	2017	262	14	8	76	24	128	12
	2018	288	22	11	89	21	137	8
	2019	351	29	16	86	28	176	16
	2020	123	12	5	17	14	69	6
Total	2nd half	1197	91	51	331	88	587	49

Note: The first half period (i.e., pre-financial reforms) begins from 26th April 2011 and ends 25th April 2016. The second half period, (i.e., post-financial reforms), spans from 25th April 2016 to 26th April 2020.

Figure 5.2 shows the announcements by industry sector over the relevant period. Because of the steady growth in the number of companies listed in the Tadawul over time, the sample is limited to observations that meet the selection criteria. Therefore, firms that did not have available data in accordance with the selection criteria are not included. For example, the REIT sector was added to the Tadawul in 2016; however, no companies were affiliated with this sector over the first half of the study period. Further, although the insurance sector was actively traded in before 2016, insufficient data are available for securities prices and trading volumes over the period of the estimation window.

Figure 5.2

Number of Announcements by Industry Sector Over the Relevant Period.



5.2.4 Historical Equity Data

The frequency of data employed in the analysis is daily data-based. This high frequency is chosen for several reasons that can be concisely summarised as follows. First, because of the objectives of this study, the analysis is carried out to identify ARs and AVs over several days surrounding the announcement date. Further, the daily selection stems from its characteristics resulting in more powerful results. Academic studies point out that when daily data observations are used, the power of event studies to detect abnormal movements is much greater than is possible with weekly or monthly observations (Kothari & Warner, 2007; MacKinlay, 1997).

Moreover, this study utilises classes of econometrics models that encourage the consideration of pure time series models, including ADL and GARCH models, and a test of ARCH effects that treat heavy demanding data. Brooks (2019) advocates that a suitable data frequency when testing for ARCH and GARCH effects is daily observations, indicating that 'models of this kind are inevitably more data intensive than those based on simple linear regressions, and … they work better when the data are sampled daily rather than at a lower frequency' (p. 426).

The dataset for each stock contains historical daily data on the market index and all stock daily prices and trading volumes, including company name, date, open, high, low, close, change, percentage change, volume traded, value traded (in SAR), and the number of trades over the 11 years from 2010 to 2020. The closing share prices are adjusted for corporate actions such as splits, spinoffs and rights. A one-year interval prior to the relevant period is required for stock data to be available for the estimation window (–240) when modelling the expected returns and expected trading volumes.

As previously explained, the study considers examining several factors that may affect the MCMs. Each factor has its own proxy, some of which are based on results from the analysis. The others require collection of data. The data collected include the common shares outstanding, volume traded and bid–ask spread for stock prices collected from the MDPRD.

5.3 Returns Event Study Analysis

Before proceeding to the empirical approach, this section provides a brief outline of the returns event study structure employed in this research. The components of the analysis can be broken down into seven procedures: (i) defining the event of interest, (ii) selection criteria, (iii) modelling ARs, (iv) the model parameters, (v) designing the framework of hypothesis testing for the ARs, (vi) presenting empirical results, and (vii) ending with interpretation and conclusions.

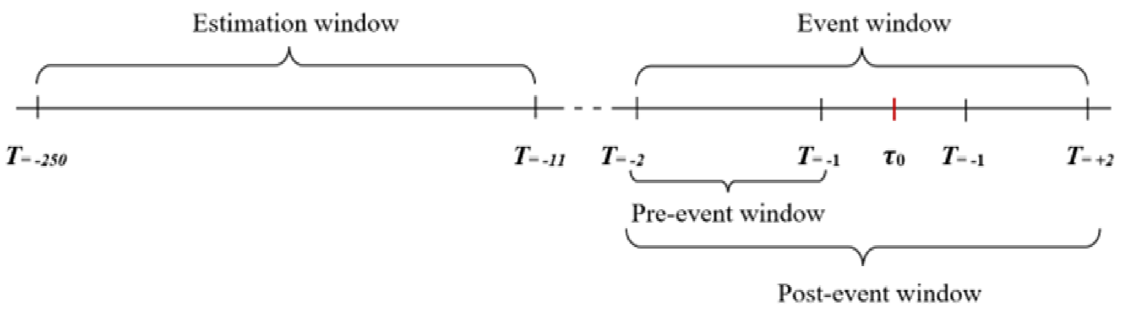
A returns event study begins by defining the event of interest and identifying the time windows relative to the event date to estimate security prices reactions associated with each individual event. Figure 5.3 shows the timeline for the event study performed for this thesis. The event date is defined as ($\tau = 0$), and there are two periods of interest for each event in the analysis. To begin with, the whole period consists of a maximum of 261 daily return observations respective to the event day.

The first period is the 'estimation window', which includes the first 240 trading days beginning at day –250 and ending at day –11 relative to the event day ($\tau = 0$). Throughout the returns analysis sections, the term estimation window is used to refer to the 240 trading days ending 10 days prior to the announcement day. The daily returns observations within the estimation window are used to estimate the model parameters for estimating ARs. Note that the estimation window is kept separate from the event window to ensure that the estimation window is not contaminated by the event window, as indicated by the middle-dashed line in Figure 5.3.

Immediately after that is the period designated the 'event window', consisting of the next 21 days. The event window starts at day –10 and ends at day +10, and it is itself divided into two windows; the pre-event window and the post-event window where each has its own particular purpose. The pre-event window is used to determine whether APPMs occurred prior to the event day. The post-event along with pre-event windows are used to investigate if there are significant changes in stock prices, which helps to determine whether there is enough evidence to classify an event as a SA. Note that the event day is included in the post-event window but is not included in the pre-event window, to capture the price movements from the event, which occurs once the announcement is released. In this event study, multiple event window lengths are used ([–2, +2], [–5, +5] and [–10, +10]), rather than an event window with a single length, to test the hypotheses proposed in Chapter 4.

Figure 5.3

Timeline of the Event Study.



The following procedure is to use the constructed data sample according to the selection criteria described in Section 5.2.3. In the constructed sample of major firms events and their respective equity data, each announcement is regarded as an event that may have an impact on the asset prices of the company. As previously mentioned, a dataset with every individual firm’s announcement is documented manually with millisecond precision. This is important because if the announcement published after the close of the market (i.e., 3:00 PM), the date of the announcement will be misidentified. In this regard, the following trading day is considered the event day ($\tau = 0$) to correctly associate it with the date on which market participants and stock prices have a chance to react to the news. In an event study analysis, it is crucial to accurately identify the date on which the event occurs and align the sample data with respect to the event date (Brooks, 2019; Campbell et al., 1998; MacKinlay, 1997).

The analysis is then applied to each individual event to assess statistically significant AR movements surrounding the event day. A common practice when conducting an event study is to pool companies into groups to examine how security prices react to a given event. However, since the present study is most interested in differentiating SAs preceded by

APPMs, rather than the average effect of ARs, the security return of each firm is estimated on an individual basis. To serve the purposes of this study, it is an event-by-event examination of pre-announcement movements that allows accurate judgement of whether APPMs have taken place ahead of SAs. It is necessary to identify each individual event as either a SA or APPM, or determine that there are no statistically significant AR movements around the event day.

To examine whether the security returns exhibit ARs, the normal 'expected return' of a given stock must be defined first. The expected return is the return that would be expected in the absence of information related to the event. According to the model selected (as discussed in Chapter 4), estimation procedures are performed to estimate the expected returns then calculate the ARs. The ARs on any given day are computed as the difference between the expected returns predicted by a model and the actual returns of stock. Therefore, the estimation window period must be defined to use its data when estimating model parameters to obtain the expected return, which is then compared with the actual return over the event window being examined.

As pointed out in Section 5.1, a returns event study employs two approaches to measuring ARs by estimating the statistical relationship between the changes in the individual security returns with considering the movements of the overall market index returns. The MM approach explained in Section 5.4 uses a SLR model to estimate securities ARs and extract inferences about ARs using the bootstrap technique.

The ADL-GARCH approach utilises the autoregressive distributed lag model (ADL) (1,1) (i.e., first order Autoregressive process) and generalized autoregressive conditional heteroscedasticity (GARCH) (1,1) process, and a combination of the ADL-GARCH. This approach extends the regression model used in the MM approach by addressing any shortcomings the MM approach might fail to consider. The goal of this approach is to enhance estimation procedures and obtain more reliable inferences when modelling ARs. Further, undesirable features detected in the sample data for this study motivate the use of the ADL-GARCH approach, which in turn overcomes potential invalid inferences from the MM approach, particularly in the presence of serial correlation and/or heteroscedasticity.

A major technical drawback associated with use of the MM approach is that it could estimate that APPMs have occurred prior to release of SAs where the occurrences of the APPMs are due to the situation of significant changes in volatility in the period leading up to announcement; or strong serial correlation in the days surrounding the period being analysed. As a result, such features encourage consideration of the use of advanced models to avoid potential misestimation of ARs.

However, whether to use ADL-GARCH models to model stock returns depends on four scenarios. The nature of the data, in conjunction with the assumptions, will determine the selection of which model that is going to be the most appropriate to use. The ADL-GARCH approach is discussed in detail in Section 5.5 with comprehensive descriptions and mathematical specifications. Briefly, to identify the best model to use with stock return data, I begin by estimating the series of ARs using the data observed from the estimation window. The time series estimates are tested for the presence of heteroscedasticity (i.e., changes in their variance) and serial correlation over the period under examination. To make the right choice on which a suitable model should be chosen, four assumptions are subjected to the following hypotheses testing framework.

First, if neither serial correlation nor heteroscedasticity are detected in the stock returns data, the simple regression model (MM approach) will be employed. Second, if the data exhibit only changes in variance across time, the ARs will be estimated via extending the MM according to the GARCH (1,1) process. Third, to control for the presence of serial correlation, the ADL model (1,1) will be fitted to estimate ARs. Fourth, if both characteristics serial correlation and heteroscedasticity are detected, a consolidation of autoregressive distributed lag with generalized autoregressive conditional heteroskedasticity (ADL-GARCH) will be employed to treat the existence of both features. After modelling the ARs, the quantile bootstrap technique is used to identify whether the APPMs and SAs meet the statistical significance threshold. For the hypothesis test, the approach employs quantile thresholds derived from a conditional bootstrap distribution.

Having illustrated how the returns event study analysis is carried out by clarifying the design and procedures applied, the next two sections are concerned with the empirical application of the MM and ADL-GARCH approaches.

5.4 Conventional Market Cleanliness Measure According to the MM Approach

Proceeding now to the empirical analysis, this section describes the application of the conventional market cleanliness measure according to the MM approach. It is worth noting that the initial three research hypotheses are tested through the fourth and fifth hypotheses. To test H_{04} and H_{05} (developed in Section 4.3.3) using the MM approach, the daily abnormal stock returns are measured by performing a standard event study methodology to stock returns and employing an OLS market model following Barwon and Warner (1985), MacKinly (1997) and Dubow and Monteiro (2006). Daily frequency observations are selected for this study for the reasons explained in Section 5.2.4. An advanced step before estimating the ARs, the security and market daily returns are calculated. Each daily stock return is computed by employing the logarithmic returns approach for observations of the price series ($P_{i,t}$) for stock *i* at time *t*. Logarithmic daily returns are computed using adjusted closing prices with consideration of dividend payments as per Equation (5.1):

$$R_{i,t} = 100\% \times ln\left(\frac{P_{i,t} + D_{i,t}}{P_{i,t-1}}\right) \quad (5.1)$$

where *ln* is the natural log; $P_{i,t}$ refers to the price of security *i* at the end of period *t*; $D_{i,t}$ denotes the dividends paid during period *t*; and $P_{i,t-1}$ is the price of security *i* at the end of period *t*–l, adjusted for any capitalisations to make it comparable to $P_{i,t}$.

The market daily returns are calculated using the logarithmic returns approach as shown in Equation (5.2). The market index Tadawul All Share Index (TASI) is used as a proxy for the market where $R_{m,t}$ refers to the index daily returns on day *t* using the TASI:

$$R_{m,t} = 100\% \times ln\left(\frac{TASI_t}{TASI_{t-1}}\right) \quad (5.2)$$

where *ln* denotes the natural logarithm; $R_{m,t}$ denotes the index daily return at time *t* and *TASI* is a proxy for the market index.

Although the method of a simple (discrete or arithmetic)[40] daily return can be used, the logarithmic return is commonly employed in the academic finance literature and is considered the most favourable for the analysis carried out in this study, for the following key reasons. Corrado and Truong (2008) suggest that tests utilising logarithmic returns tend to yield superior test specifications relative to tests utilising arithmetic returns. Further, Hudson and Gregoriou (2015) and Brooks (2019) offer relatively recent summaries of the large body of literature in this area. They find that logarithmic returns have the advantage that they can be extrapolated to find continuously compounded returns. This means that the frequency of compounding of the return does not matter; therefore, the returns over stocks are more easily comparable (Hudson & Gregoriou, 2015). Moreover, as this study uses models that take into

[40] The simple return method is defined mathematically as $\boldsymbol{R_{it} = \frac{P_{it}+D_{it}-P_{it-1}}{P_{it-1}} \times 100\%;}$ where: R_{it} denotes the simple return of a share *i* on trading day *t*, P_{it} is the closing price of stock *i* on day *t*. To adjust a stock price time series, the dividends are added where D_{it} is the dividend paid to shareholders of stock *i* on day *t*.

account the presence of heteroscedasticity and serial correlation, thus, taking the logarithm is helpful for rescaling the return data, which makes their variance more constant. In this way, statistical issues around heteroscedasticity and serial correlation cab be remedied using the logarithm approach (Brooks, 2019).

In the same vein, Strong (1992) provides theoretical and empirical arguments in favour of the use of logarithmic returns method. From a theoretical perspective, the author indicates that ‘logarithmic returns are analytically more tractable when linking together sub-period returns to form returns over longer intervals’. From an empirical aspect, ‘logarithmic returns are more likely to be normally distributed and so conform to the assumptions of standard statistical techniques’ (Strong 1992, p. 535). This argument is in line with Brooks (2019), who suggests that logarithmic method produces a distribution that is positively skewed and closer to a normal distribution. Note that the dividend payments variable is integrated into Equation (5.1), which is essential to be considered because failure to do so would have a significant negative effect on the cumulative abnormal returns over a prolonged period. Neglecting the calculation of dividend payments could cause an underestimate in total returns that come to investors, as explained by Brooks (2019). Having dealt with calculation of the daily returns of the securities and market, the following section explains the estimation of ARs.

5.4.1 Estimation of Abnormal Returns

The logarithmic method is utilised in the computation of the daily returns for the market and the securities for the reasons stated above. The next procedure is to begin estimating the ARs to assess an event’s impact on stock returns, after first obtaining the expected returns. This is done by estimating the statistical relationship between the security and the market return using daily data for the stock return and TASI return over the estimation window. The MM approach uses the market model, which relates the return of a stock to the market portfolio return. To obtain the expected return E ($R_{i,t}$) for security i on day t, a SLR model is calculated for each firm's event to estimate the model coefficients and the residual variance by regressing the security return on the index return over the estimation window, as shown in Equation (5.3):

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \varepsilon_{i,t} \tag{5.3}$$

where $R_{i,t}$ is the return on security i at time t, $R_{m,t}$ denotes the return of the market portfolio in the period t and $\varepsilon_{i,t}$ is the zero-mean disturbance term. Parameter *ß* depicts how much the stock return is influenced by the overall movements of the market portfolio returns over the estimation window. The model parameter α denotes the expected value of the security daily return after controlling for all market movements over the estimation window. This simple model supposes that ε (the estimation error) has standard statistical properties (a zero-mean independently and identically distributed error). Therefore, the coefficients $\hat{\alpha}_i$ and $\hat{\beta}_i$ estimated from the model are used to calculate the expected returns for stock i on day t as shown in Equation (5.4):

$$E(R_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \tag{5.4}$$

Having obtained the expected returns for the estimation window (t = −250, …, −11), the ARs of the security on a given day are computed by subtracting the expected asset return, predicted by Equation (5.4), from the actual asset return as expressed in Equation (5.5):

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{5.5}$$

5.4.2 Calculating the Cumulative Abnormal Returns

Because there may be large variation in the stock returns around the days that fall within the event window, with the price likely to increase on some days and decrease on others, it might be difficult to distinguish overall patterns. However, such patterns can be measured accurately by calculating the time series cumulative abnormal returns (CARs) over multiple days across the event window. Specifically, the CARs are computed by summing the ARs over the event window days.

Before proceeding to explain how the CARs are calculated, it is worth noting that when undertaking a returns event study to gauge the effects of an event, one of the key points is whether to consider the use of CARs or buy-and-hold ARs (BHARs).[41] The BHAR approach has been subject to criticism for its tendency towards 'pseudo-timing' as it systematically underperforms in response to clustering of issues affected by a common event (Kothari & Warner, 2007). Further, Fama (1998) argues theoretically and statistically in favour of the utilisation of CARs rather than BHARs, pointing out that the BHARs method appears to be more adversely influenced by skewness in the sample of ARs. According to Fama (1998), 'BHARs can grow with the return horizon even when there is no abnormal return after the first period' (p. 294). Similarly, Mitchell and Stafford (2000) indicate that the BHARs method can produce a false conception of the speed at which prices adjust in response to an event.

These issues motivate consideration of the use of the CAR rather than the BHAR method. Proceeding now with the method used to calculate CARs, the ARs for a given day t for firm i, obtained by Equation (5.5), must be aggregated to derive inferences about the effect of the event being examined. The ARs observations are aggregated to produce the CARs. 'The concept of a cumulative abnormal return is necessary to accommodate a multiple period event window', as demonstrated by MacKinly (1997).

The event window is expanded to encompass several trading days surrounding the event day ($\tau = 0$). However, as mentioned earlier, two windows (i.e., the pre-event window

[41] The formula of the BHAR is mathematically expressed as ${}^{(t_1,t_2)}BHAR_i\ [\prod_{t=T_1}^{T_2}(1 + R_{i,t}) - 1] - [\prod_{t=T_1}^{T_2}(1 + E(R_{i,t}) - 1]$ as per Brooks (2019).

and the post-event window) fall within the event window period. The event day ($\tau = 0$) is included in the post-event window to evaluate changes in prices that occur after the event day, which helps to determine whether the announcement can be classified as a SA. The event day is excluded from the pre-event window to isolate the impact of the event; that is, this window is used to investigate whether the event experienced APPMs.

As pointed out in Section 5.2, the event window length is designed to consist of multiple event windows of varying durations—(−2, +2), (−5, +5) and (−10, +10)— used in this study to test the relevant hypothesis (i.e., H_{03}) developed in Section 4.3.2. However, the explanation here focuses on an event window with length of (−5, +5). Chapter 6 presents findings for the other lengths. The CARs over the post-event window days are computed using Equation (5.6), and Equation (5.7) calculates the CARs across the pre-event window:

$$^{(\tau_{-5},\tau_{+5})}CAR_i = \sum_{t=\tau_{-5}}^{\tau_5} AR_{it} \tag{5.6}$$

$$^{(\tau_{-5},\tau_{-1})}CAR_i = \sum_{t=\tau_{-5}}^{\tau_{-1}} AR_{it} \tag{5.7}$$

Broadly, when examining CARs with an event window of any length, two windows are examined for each length. For example, for an event window with length (−5, +5), the first CAR, described by Equation (5.6), stands for the total $^{11}CAR_i$ calculated over the entire event window period (i.e., post- and pre-event periods). The second CAR, described by Equation (5.7), stands for $^{-5}CAR_i$, which denotes the CAR of the pre-event window. In other words, the post-announcement $^{(-5,+5)}CAR_i$ includes the total CARs for the 11 trading days across the event window as well as the event day ($\tau = 0$). The pre-announcement $^{(-5,-1)}CAR_i$ consists of only the five trading days preceding the day of the announcement, excluding the event day. To investigate whether the CARs of both pre- and post-event windows for a particular event are statistically significant, a bootstrap method using a defined quantile threshold is employed, as described in the next section.

5.4.3 The Bootstrap Method

To test H_{04} and H_{05}, (developed in Section 4.3.3), the bootstrap statistical test is employed to examine whether the actual CARs (−5, +5) for the post-event window and the actual CARs (−5, −1) for the pre-announcement window associated with a specific event are statistically significant. The test estimates the sampling distribution using random sampling with replacement. More precisely, the bootstrap technique estimates the finite sample distribution of the sequence of ARs from the estimation window observations and compares the magnitude of the actual post-event CARs and the actual pre-event CARs with their respective simulated empirical distribution values generated by bootstrapping. The simulated 11-day CARs simulate the post-event window CARs (i.e., five days before and five days after the announcement day, plus the day of the announcement). The simulated five-day CARs simulate the pre-event window CARs (i.e., five days before the event day). This technique helps judge whether the CARs over the post- and pre-event period are statistically significant. Application of the bootstrapping method involves performing seven steps:

1. Taking the daily data observations for each security return during the estimation window (−250 to −11) for every announcement and calculating the daily AR for each day in the estimation window by subtracting the actual stock returns on each day from the expected returns.
2. Drawing random sequences of 11 ARs from the estimation window, then summing them to compute simulated 11-day CARs as described in Equation (5.8).
3. This process is repeated 50,000 times to generate 50,000 randomly simulated 11-day CARs.

4. The actual post-event window CARs are used to examine whether there is sufficient evidence to classify the announcement as a SA. The CARs of the post-event window are assumed statistically significant at the 1% level if they are lower than or equal to the 0.5% quantile of the simulated total 11-day CAR ($^{11}CAR_i^*$) or greater than or equal to the 99.5% quantile of the simulated total 11-day CAR ($^{11}CAR_i^*$).[42] In other words, the actual CAR for the post-event window is considered statistically significant at the 1% level if it is less than or equal to the 250th most negative generated total 11-day CAR or greater than or equal to the 250th most positive simulated total 11-day CAR. If the announcement meets the specified high statistical threshold, it is classified as a SA. This is the definition of the SA.
5. Once a SA has been identified, similar procedures are used for the pre-event window CARs, with two differences, to investigate whether APPMs took place during the pre-event window. Steps 1 and 3 are repeated with a focus only on events statistically identified as SAs (i.e., less than or equal to the 250th most negative or greater than or equal to 250th most positive).
6. The change made to Step 2 implies that instead of selecting 11-day ARs, the analysis involves dragging five-day ARs at random then summing them to compute a simulated five-day CAR as shown in Equation (5.9).
7. The change made to Step 4 is that the actual five-day CARs associated with the event are compared with the simulated 50,000 $^5CAR_i'$ generated by bootstrapping.[43] The actual five-day CARs are deemed statistically significant at the 10% level if they are greater than or equal to the 90% quantile of the simulated ($^5CAR_i'$) or less than or equal to the 10% quantile of the simulated ($^5CAR_i'$) (i.e., lower than or equal to the

[42] The asterisk notation * is to denote to the simulated eleven-day samples extracted from the bootstrap not the actual CARs.
[43] The prime symbol $'$ is to denote to the simulated five-day samples extracted from the bootstrap not the actual CARs.

50th most negative or greater than or equal to the 50th most positive simulated five-day CARs).

The bootstrap technique produces detailed information about the distribution of the event window CARs and the pre-event window CARs for each event. A simulated 11-day CAR, ${}^{11}CAR_i^*$ described by Equation (5.8), and a simulated five-day CAR, ${}^{5}CAR_i'$, described by Equation (5.9), are computed for each individual event using the values generated by bootstrapping. Thus, the productions generated from this method are assessed to decide whether the post-event window CARs and the pre-event window CARs are statistically significant:

$$ {}^{11}CAR_i^* = \sum_{\hat{f}=1}^{11} AR_{i,f}^* \tag{5.8} $$

$$ {}^{5}CAR_i' = \sum_{\hat{f}=1}^{5} AR_{i,f}' \tag{5.9} $$

After running the two bootstraps through all the firms announcements, a hypothesis testing framework is established to determine whether there is sufficient evidence to draw a conclusion that the ARs across the post-event window (CARs of the period[11]) were significantly influenced by the event and the variation in stock prices is significantly different from the expected return. Under null hypothesis H_{04}, the announcement had no significant impact on the distribution of CARs over the post-event window. If the test leads to rejection of the null, the event is classified as a SA, which indicates that the announcement contains significant news and is statistically significant.

Having identified SAs that were affected by the event, a further hypothesis test is conducted to examine the null hypothesis associated with the CARs distribution over the pre-event window. Under null hypothesis H_{05}, the event had no significant impact on the distribution of CARs over the pre-event window. If the null hypothesis is rejected, this suggests that the event experienced APPMs if price movements in the pre-event window are in the same direction as those in the post-event window and significantly different from normal movements. Thus, the event is defined as an APPM, which likely indicates that potential insider trading activities have occurred.

5.4.4 Calculating the Market Cleanliness Measure

The previous sections present the methods used to draw conclusions about the events statistically classified as SAs and preceded by APPMs. Thus, the market cleanliness measure is calculated as the ratio of SAs preceded by APPMs and can be mathematically expressed as in Equation (5.10):

$$Market\ Cleanliness\ Measure = \frac{\sum APPMs}{\sum SAs} \tag{5.10}$$

To achieve the first objective of the study, based on the MM approach, which seeks to estimate the level of potential insider trading in the Tadawul based on the returns event study of the MCMs in the periods both before and after the introduction of the financial reforms, the MCMs for the samples from the pre- and post-reform periods are calculated as per Equation (5.10). To test the first main research hypothesis (MH_{01}), which postulates that the difference in the MCMs between the two periods is not statistically significant, a statistical test of the difference in the ratio of APPMs between the two periods (i.e., before and after 25 April 2016) is performed using the *z*-test described in Equation (5.11):

$$Z = \frac{P_1 - P_2}{\sqrt{PQ(n_1^{-1} + n_2^{-1})}} \tag{5.11}$$

The test assumes that each event in a particular sample has the same probability of being an APPM regardless of other explanatory variables (i.e., the chance of an event occurring is not dependent on other events). If n_1 is the number of observations in set *1*, P_1 is the probability of an event being an APPM, $Q_1 = 1-P_1$, $n_1 P_1 \geq 5$ and $n_1 Q_1 \geq 5$ where P and $Q = 1-P$ are the average ratios for both samples. To test H_{03}, which states that the difference in the MCMs between the two periods is insignificant regardless of the length of the event window, a preliminary analysis is carried out to estimate the MCMs for the pre- and post-reform periods using several event window lengths: (−2, +2), (−5, +5) and (−10, +10). The *z*-test is used to test if there are significant differences in the MCMs calculated for different event window lengths.

In sum, this section demonstrated the model used and the procedures performed to estimate the MCMs using the MM approach. However, despite its feasibility and efficacy, the MM suffers from a drawback concerned with undesirable characteristics found in the study data. Thus, the next section described a more sophisticated approach that overcomes the limitations of the MM approach and re-examines the research hypotheses tested in this section.

5.5 Advanced Market Cleanliness Measure According to the ADL-GARCH Approach

This section provides a clear justification for considering four scenarios that utilise a wide range of advanced models and diagnostic tests motivated by data features observed in the sample of the present study. The market model in its basic version as employed in the MM approach and described in the previous section uses OLS to estimate the linear model as expressed in Equation (5.12). The OLS estimation relies on the assumption that the estimation errors of the ARs have the standard statistical properties of zero expected value, constant variance over time and independence from the estimation errors across the period:

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{m,t} + \varepsilon_{i,t} \tag{5.12}$$

However, it is possible that the model in this version may be unable to fulfil the homoscedasticity and non-serial correlation of errors assumptions because these assumptions might not hold for some features of the time series data of this study. To be more specific, the variance (heteroscedasticity) in the daily ARs change over time for some securities and their ARs are not dependent (serially correlated). With respect to the changes in variance resulting from volatility, Gujarati and Porter (2009) indicate that the estimated variances of OLS estimators are significantly affected by increases in variance.

Chapter 4 comprehensively reviews studies that raise concerns about the validity of OLS in the presence of heteroscedasticity and serial correlation. To reiterate, Brown and Warner (1985) identify potential issues related to the time series characteristics of daily data and provide empirical evidence that the β parameter of the OLS market model is biased across an event window longer than one day. Furthermore, Scholes and Williams (1977) indicate that with nonsynchronous trading of securities, OLS estimators of market model parameters are inconsistent and biased when using daily data. For example, for shares that are infrequently traded, the market model β is downward biased and vice versa.

In the context of the standard event study method, ignoring the effects of high autocorrelation or volatility can cause hypothesis tests to be misidentified. Brown and Warner (1985) point out that 'the failure to take into account autocorrelation in estimating the variance of the cumulative mean excess return could result in misspecification' (p. 19). With respect to changes in variance, Engle (2001) indicates that, 'the regression coefficients for an ordinary least squares regression are still unbiased, but the standard errors and confidence intervals estimated by conventional procedures will be too narrow, giving a false sense of precision' (p. 157).

Given the findings of the extensive review of the literature in Chapter 4, it is thus imperative to designate procedures to determine whether the securities data experience serial correlation or/and heteroscedasticity and recognise their respective implications for the event study analysis conducted in this study.

The use of a model that does not consider these assumptions (i.e., the presence of serial correlation and/or heteroscedasticity) may lead to incorrectly estimated ARs and thus derivation of unreliable inferences, contaminating judgements about the MCMs. The development of a complex model helps to better depict the stylised characteristics of serial correlation and volatility. Table 5.2 summarises the application of the four possible scenarios and their respective time series models. Table 5.3 presents the statistic tests conducted to test hypotheses and decide which model is the most suitable based on the presumed scenarios in alignment with data features.

Table 5.2

Description of the Scenarios and Corresponding Models Utilised for Each Scenario.

Scenario description	**Designated model**
Neither Serial Correlation nor Heteroscedasticity	Simple Linear Regression
Presence of only Heteroscedasticity	GARCH (1,1) model
Presence of only Serial Correlation	ADL (1,1) model
Presence of both Serial Correlation and Heteroscedasticity	ADL-GARCH model

Table 5.3

The Null Hypotheses and Test Statistic Used.

Null Hypothesis	**Used Tests**
H_{05a}: There is no heteroscedasticity.	Engle’s LM (Lagrange multiplier test).
H_{05b}: There is no serial correlation.	Durbin Watson test, Wald test, Chi-Square test.

In this section, the basic concepts of the ADL-GARCH approach are explained with justifications that encourage the use of this approach. This section discusses the four scenarios related to data characteristics, and what can be done to handle problems of heteroscedasticity and serial correlation. The next section discusses in greater detail the mathematical specifications, procedures for utilising the appropriate model and statistical tests for robust techniques to model ARs.

5.5.1 Estimating Abnormal Return According to the ADL-GARCH Approach

Having discussed above the four classes of model for the purposes of handling undesirable features found in data returns, this section on estimating ARs discusses scenarios concerned with constructing the proposed models for improving AR estimation following the advanced market cleanliness methodology developed by Monteiro et al. (2007). Before proceeding to examine which class of model should be employed, three steps are taken: first, calculation of the security and market daily returns; second, performance of the simple market model; and third conducting of statistic tests for hypotheses testing as shown in Table 5.3 using the productions predicted by the market model to identify which assumptions hold.

The daily return for each security and the market return are calculated using the logarithmic returns approach as expressed in Equation (5.1) and Equation (5.2), respectively (described in Section 5.4). To test H_{04} and H_{05} using the ADL-GARCH approach, the security daily ARs are estimated by performing a standard event study using daily stock returns. The market model is employed under the assumption of an OLS as expressed in Equation (5.13):

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + u_{i,t} \tag{5.13}$$

Although the statistical model in Equation (5.13) holds the assumption that the security returns are IID through time, as illustrated by MacKinly (1997), this assumption is likely violated by some time series data observed over the period being examined. Specifically, the residuals $u_{i,t}$ in event time are assumed to be IID; however, in the presence of serial correlation or changing variance (volatility), the residuals would not be IID. There is evidence that increases in variance could lead to misleading results if not considered, as previously discussed in Chapter 4.

To determine whether the residuals predicted by the conventional OLS estimates described in Equation (5.13) suffer from conditional heteroscedasticity, the Engle's LM test is computed to test for ARCH (1) effects. If the test fails to reject null hypothesis H_{05a}, which assumes that daily variance in the estimation errors of the market model is constant over time, the OLS market model error terms have a constant variance (i.e., homoscedastic). Conversely, under the alternative hypothesis, if the test results reveal that the data show heteroscedasticity, the null hypothesis must be rejected because the data are heteroscedastic as a function of the ARCH (1) effect.

To verify whether the residuals predicted by Equation (5.13) are serially correlated, the first procedure assumes that the residuals are not serially correlated over the stock return. To test null hypothesis H_{05b}, that the error term is not serially correlated, the analysis considers the following tests statistics: the Durban–Watson test, LM test using the 'R' program (R programming language for statistical computing). The Durban–Watson test is computed by calculating the Wald statistic for the parameters of the lagged residuals in an auxiliary OLS regression as proposed by Brooks (2019). If the null is not rejected, this implies that there is no serial correlation. Having providing explanation for the test used, four scenarios are now examined.

The first scenario relates to announcements where the null hypotheses (i.e., H_{05a} and H_{05b}) are not rejected because both the Durban–Watson and Engle's tests reveal the absence of both serial correlation and heteroscedasticity; this indicates the OLS assumption holds. Therefore, the linear regression model described by Equation (5.14) is applicable because there is no violation of the assumption that the residuals $u_{i,t}$ described in Equation (5.13) are IID. Specifically, there is no serial correlation in the error terms and the estimate of the β

parameter will not be affected; that is, there is no change in variance (heteroscedasticity). In this case, it is useless to utilise advanced models that deal with the presence of serial correlation or heteroscedasticity. The expected returns of the securities can be obtained by

$$\hat{R}_{i,t} = \hat{\alpha}_i + \hat{\beta}_i R_{m,t} \tag{5.14}$$

Then, the AR ($AR_{i,t}$) for each stock i on day t is computed as the actual return of the stock minus the expected return over the period as in Equation (5.15):

$$AR_{i,t} = R_{i,t} - \hat{R}_{i,t} \tag{5.15}$$

To ensure that the AR is following the standard normal distribution asymptotically, the following equation is used:

$$SAR_{i,t} = \frac{R_{i,t} - \hat{R}_{i,t}}{\sqrt{\widehat{\sigma_t^2}}} \tag{5.16}$$

The discussion now moves on to investigate the second scenario in which Engle's LM test for ARCH effects leads to rejection of null hypothesis H_{05a}, revealing the existence of heteroscedasticity, but where the Durban–Watson test suggests no presence of serial correlation. The ARs are modelled using Equation (5.13) but recognising that the variance in estimation errors is changing across time because of a GARCH (1,1) process. The GARCH model is described by Equation (5.17) and (5.18):

$$u_{i,t} = \sigma_{i,t}\eta_{i,t} \tag{5.17}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i u_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2 \tag{5.18}$$

Using the residuals from Equation (5.13), the GARCH model is estimated by Equation (5.19) for the estimation window period (t = –250, –11) and Equation (5.20) for the event window period (t = –9, +10).[44] Thereafter, Equation (5.15) is utilised to compute the ARs, and Equation (5.16) is used to obtain the standardised ARs:

$$\hat{\sigma}_{i,t}^2 = \widehat{\omega}_i + \hat{\alpha}\hat{u}_{i,t-1}^2 + \hat{\beta}\hat{\sigma}_{i,t-1}^2 \tag{5.19}$$

$$\hat{\sigma}_{i,t}^2 = \widehat{\omega}_i + \hat{\beta}\hat{\sigma}_{i,t-1}^2 \tag{5.20}$$

Turning now to the third scenario where tests lead to rejection of null hypothesis H_{05b}, suggesting the presence of only serial correlation (i.e., the ARs are serially correlated). The ARs are estimated using an autoregressive distributed lag ADL (1,1) model as described by Equation (5.21) to remedy the issue of serial correlation:

$$R_{i,t} = \pi_i + \lambda_i R_{m,t} + \gamma_i R_{i,t-1} + \delta_i R_{m,t-1} + \epsilon_{i,t} \tag{5.21}$$

The ADL (1,1) model in Equation (5.21) is estimated using Equation (5.22) where $\hat{\pi}_i$ denotes the intercept of the equation, $\hat{\lambda}_i$ refers to the effect of the market return, $\hat{\gamma}_i$ is the effect of the lagged security return and $\hat{\delta}_i$ is the effect of the lagged market return. Consequently, Equation (5.15) and (5.16) are used to obtain the ARs and standardised ARs, respectively.

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[44] As explained in Section (5.2) that the event window comprises ten days before the event day and 10 days after the event day; however, we use (t = -9) because of the lag.

$$\hat{R}_{i,t} = \hat{\pi}_i + \hat{\lambda}_i R_{m,t} + \hat{\gamma}_i R_{i,t-1} + \hat{\delta}_i R_{m,t-1} \tag{5.22}$$

Turning now to the fourth scenario, in which the Engle's LM and Durban–Watson tests indicate that both heteroscedasticity and serial correlation exist, the expected returns are computed using a GARCH (1,1). Equation (5.19) and (5.20) are utilised to control for heteroscedasticity and ADL (1,1) Equation (5.22) to control for serial correlation. Then, Equation (5.15) is utilised to calculate the ARs, and Equation (5.16) is used to obtain the $SAR_{i,t}$ for asset i on day t.

5.5.2 Calculating the Standardised Cumulative Abnormal Return

Having tested sub-hypotheses H_{05a} and H_{05b}, the analysis moves on to investigate whether there is evidence that the SAs were preceded by APPMs. The bootstrap technique described in Section 5.4.3 is employed here to test H_{04} and H_{05}. An aggregation of SARs is necessary to draw conclusions about the impact of a certain event on security returns. Observations of SAR are aggregated in two dimensions. The first occurs across each individual stock, and the second accumulates the SARs over the event window observations. By summing the SARs for the period being examined, the standardised cumulative abnormal return (SCAR), as explained by Brooks (2019) and Kolari and Pynnonen (2011), is obtained for each announcement over the post-event window, as shown in Equation (5.23), and the pre-event window as shown in Equation (5.24):

$$^{(\tau_{-5},\,\tau_{+5})}SCAR_i = \sum_{t=\tau_{-5}}^{\tau_5} SAR_{i,t} \tag{5.23}$$

$$^{(\tau_{-5},\,\tau_{-1})}SCAR_i = \sum_{t=\tau_{-5}}^{\tau_{-1}} SAR_{i,t} \tag{5.24}$$

Two windows are investigated: (i) the SCARs across post-event window days; and (ii) the SCARs over the pre-event window. The SCAR described by Equation (5.23) is the total $^{11}SCAR_i$, which relates to the post-event window period. The SCAR described by Equation (5.24) is the $^{-5}SCAR_i$, which is the SCAR for the pre-event window. In other words, the post-announcement window $^{(-5,+5)}SCAR_i$ includes the total SCARs of the 11 trading days across the event window, including the event day (τ = 0). The pre-announcement window $^{(-5,-1)}SCAR_i$ relates only to the five trading days ahead of the day of the announcement, excluding the event day (τ = 0).

After running the two bootstraps for all firms announcements, a hypothesis testing framework is designed to determine whether there is sufficient evidence to conclude that the SARs across the event window (SCAR of the period^{11}) are significantly influenced by the event and the variation in stock prices is significantly different from the expected return. Under null hypothesis H_{04}, the stock returns are not affected by the event. If the test leads to rejection of the null, the event is classified as a SA, which indicates that the announcement contains significant news and is statistically significant.

Having identified SAs affected by the event, a further hypothesis test is conducted to examine if the SARs over the pre-event window (SCAR of the period^{-5}) is statistically significant. Under null hypothesis H_{05}, there are no statistically significant SCARs during the pre-event window. If the null hypothesis is rejected, this suggests that the event experienced

APPMs if the price movements in the pre-event window are significantly different from normal stock behaviour and are in the same direction as the post-event window movements. In this case, the event is defined as an APPM, which indicates that potential insider trading activities are more likely to have occurred.

Having identified the numbers of SAs and APPMs, the MCMs according to the ADL-GARCH approach can be computed by dividing the total number of APPMs on the total number of SAs as expressed by Equation (5.10) (see Section 5.4.4). To test M_{H01} and H_{03} based on the outcomes of the ADL-GARCH approach, the *z*-test described in Equation (5.11) is performed.

5.6 Investigating the Effects of Selected Specific Factors on Market Cleanliness Measures

It is important to ensure that the MCMs are not influenced by other factors. Therefore, this section describes in more detail the seven factors discussed in Chapter 4 that may influence measures of market cleanliness. These factors include firm size, stock volatility, stock liquidity, information asymmetry, trading activity, the actual size of the CARs over the event window, and industry variables. The analysis investigates whether changes in these factors may influence the MCMs, which in turn helps with appropriate consideration of these factors' effects. Table 5.4 presents the sample-specific factors and the proxy for each factor considered to examine its potential impact on the MCMs.

Table 5.4

Description of the Sample-specific Factors.

Factors	Poxy	Potential effect on the market cleanliness measure
Firms' size	Market value of equity (MVE)	Although advanced market regulation may reduce possible differences in reporting conduct and insider control among various sizes companies, larger companies may reveal material sensitive information that has impact on the price more accurately and monitor insiders efficiently more than smaller companies.
Stock volatility	Variance of returns	The estimates of market model and bootstrap methods may not enough efficient in periods of high volatility.
Information Asymmetry	bid-ask price	If significant announcements affect bid-ask spreads, a big spike surrounding the event day would be exhibited.
Liquidity	Volumes traded/ outstanding shares	For illiquid stocks, the β estimate in the market model could be biased downwards which means that the measured abnormal return is higher and expected return is lower and may lead in increasing the probability that announcements or informed trading movements were successfully considered as significant by the used test. Nevertheless, illiquidity may make it more difficult to hid insider trading.
Absolute size of the mean return in the event window surrounding an event	Mean absolute abnormal return	The higher the absolute mean return in the event period, the larger are the potential gains from insider trading.
Trading activity	Average daily volume in the event window around an announcement	Abnormal pre-announcement price movements are commonly to be accompanied by a notable surge in trading volume during the days preceding the significant announcement.
Company industry affiliation	Industry dummy variable	The impact of announcements on the expectations of shareholders regarding the value of a firm, and thus, stock prices may differ across different industries. Some industries could be more accessible for insider trading than others because there are more chances for insider trading.

For the announcements sample, an analysis is carried out to determine whether any change in the likelihood that an APPM took place prior to a SA might be explained by certain sample-specific characteristics. To test H_{06} developed in Section 4.3.5, a logistic regression model similar to that used by Monteiro et al. (2007) is employed to control for the potential effects of sample-specific factors. The logit model specifications are expressed in Equation (5.25):

$$Logit\ (P_{APPM}) = log\ \left(\frac{P_{APPM}}{1-P_{APPM}}\right)$$

$$= \alpha_0 + \beta_1\ firm\ size + \beta_2\ volatility + \beta_3\ information\ asymmetry + \beta_4\ liquidity + \beta_5\ absolute\ mean\ post\text{-}event\ day\ CAR + \beta_6\ trading\ activity + \beta_7\ industry\ group + \beta_8\ 2016\ dummy \qquad (5.25)$$

The dependent variable in the above equation, $log\ (P_{APPM}\ /\ (1\text{-}P_{APPM}))$, denotes the log of the odds ratio for the probability that APPMs occurred to the probability that they not. It is computed as the logged odds ratio of P_{APPM} to 1-P_{APPM}. An odds ratio of 1 implies equal probability of occurrence of an APPM to non-occurrence. If the odds ratio is greater than 1, this suggests that an APPM is more likely to have occurred. Conversely, an odds ratio of less than 1 indicates that the probability of incidence of an APPM is less likely to have occurred. Two types of independent variable are included in the model. The first is the sample-specific factors presented in Table 5.4. The second is a period dummy for 2016 for post-reforms. A statistically significant positive coefficient would suggest that the level of potential insider trading declined in the post-reform period, whereas a statistically significant negative coefficient would indicate the opposite.

5.7 Volume Event Study Methodology

The preceding suction describes the returns event study method applied in the current study. As pointed out in Chapter 4, in addition to performing a returns-based event study this research investigates whether the stock trading volumes exhibit abnormal trading volumes by conducting the event study method for trading volumes. Security price reactions ahead of the release of new information can provide valuable insights into how insider trading activities affect price formation, and suspicious trading prior to corporate announcements may extend to impact trading volume patterns.

Following Monteiro et al. (2007), the volume event study approach is applied along similar lines to the returns event study described in Section 5.3, but with several changes. The first change is that instead of measuring ARs based on observing the price data, the volume market cleanliness measures (VMCMs) used to test for proof of abnormal pre-announcement volumes (APAVs) prior to SAs. The second modification concerns the procedures conducted to estimate expected volume (described in further detail in Section 5.7.1). The calculation of abnormal volumes (AVs) is computed for each individual stock by subtracting the expected volume, predicted by the used model, from the actual volume traded on every trading day involved in the estimation window.

The third change is the design of the length of the estimation window period where it designated to comprises 180 trading days (starting at day –250 and ending at day –71) following Monteiro et al. (2007). The length of the event window is restricted to five trading days starting with day –2 and ending at day +2 relative to the event day ($\tau = 0$). The bootstrap method is employed in trading volume analysis in the same manner as in the analysis of returns with focus on data of trading volumes (see Section 5.4.3). The CAVs over the post-event window and the CAVs across the pre-event window are calculated to identify the SAs that were proceeded by APAVs, respectively.

To this point, this section provides an introductory discussion about the trading volume event study approach used in this study. The following section describes the procedures employed to model AVs.

5.7.1 Procedures to Estimate Abnormal Volume

Before proceeding to estimate the AVs, this section sheds light on four important features of the analysis: (i) the trading volume metrics, (ii) the volume data characteristics,

(iii) the day-of-the-week effect in stock market volume and volatility, and (iv) possible ways to cope with autocorrelation and heteroscedasticity. Based on the literature review presented in Chapter 4, the trading volume measure chosen for this study is the daily number of shares traded over the period being analysed. Further, Chapter 4 reviews a number of trading volume event studies that provide empirical evidence that raw trading volume data possess undesirable statistical properties including a distinct departure from a normal distribution.

Volume data is distinctly non-normal, creating potential methodological issues, The most common way to mitigate this problem is to take the natural log transformation (Yadav, 1992). It is documented that the volume of trading surrounding an event is positively skewed. Ajinkya and Jain (1989) find that the distribution of prediction errors for the untransformed volume measurements used in their analysis displays significant deviation from normality and is substantially positively skewed, with the left tail extremely thin and the right tail fat (i.e., the mean is significantly greater than median). This affirms positive median skewness and kurtosis for the whole sample and significant departures from normality.

In applying the market cleanliness methodology, Monteiro et al. (2007) document that without transformation, the daily trading volume is not normally distributed. In their analysis the daily trading volume data without log transformation had very different mean (4,139,944) and median, (1,099,392) values; skewness of 3.89, demonstrating the distribution was right skewed; and kurtosis of 31.79, showing that it was leptokurtic (with a long-tailed or high centre peak). Following log transformation, the mean and median declined to 13.33, 13.92, respectively, and skewness and kurtosis became –0.60 and 6.21, respectively. The work of Monteiro et al. (2007) is in line with the landmark studies of Ajinkya and Jain (1989) Meulbroek (1992) who demonstrate that raw trading volume data are highly non-normal but that log transformation yields trading volume data that are approximately normally distributed. They conclude that, in general, the use of log transformation with daily trading volume data in event studies is straightforward.

Accordingly, it is necessary to remedy the implications of non-normality of trading volume before proceeding to model the AVs in the present study. Thus, natural log transformation is performed for the raw trading volume data as this is a common practice that yields a high degree of normality according to numerous studies (e.g., Ajinkya & Jain 1989; Chae, 2005; Cready & Ramanan, 1991; Monteiro et al., 2007; Wu, 2019).

The next important aspect regarding trading volume analysis is that the financial literature broadly demonstrates a day-of-the-week effect in stock market volume and volatility. For instance, Ulussever et al. (2011) examine the presence of the day-of-the-week effect in the Tadawul and find that most trading takes place in the first four trading days of the week. Moreover, the Saudi capital market is classified as an emerging market, and the Tadawul is found to be subject to seasonal effects. For example, Wasiuzzaman (2018) finds that during the Hajj pilgrimage season, the Tadawul experiences a significant increase in volatility. Further evidence provided by Seyed et. all (2005) documents a decline pattern in trading activity impacted by Ramadan. Therefore, day-of-the-week dummies are incorporated in the models used to estimate the AVs.

Another factor to consider in the analysis of trading volume is that the AVs might be more volatile during the event window or impacted by the effects of strong serial correlation. It is found that abnormal trading volumes investigated in event studies using models that do not recognise the presence of serial correlation and high volatility are severely biased downwards (Chae, 2005; Monteiro et al., 2007). According to Ajinkya and Jain (1989), 'a positive autocorrelation in the residuals implies that if the variance of multi-day residuals (or prediction errors) is computed assuming independence across days, the computed variance will be biased downwards' (p. 350).

Further, as pointed out in the preceding paragraph, the Tadawul experiences high volatility during the Hajj and Ramadan seasons. Thus, recognising the need for correction of such issues is crucial. The analysis of trading volume thus is carried out by mapping four reasonable scenarios that involve use of four classes of econometric model to overcome the presence of serial correlation and heteroscedasticity. This procedure provides very significant information about the VMCMs; the measure is found to be severely impacted if such treatments are not applied (see Section 6.4). The procedure offers an effective way to draw meaningful conclusions when modelling AVs and assessing the VMCMs.

To conclude this section, four important factors are addressed in this section. First, the selected trading volume measure used in this trading volume event study. Second, the issue of non-normality of trading volume data and the method used to deal with data that are approximately normally distributed. Third, the day-of-the-week effect in stock volume. Fourth, the issue of serial correlation and high volatility, along with a summary of correction procedures to handle the effects of these undesirable features.

5.7.2 Estimating Abnormal Volume

Returning to the core concept of trading volume analysis, this trading volume event study examines the extent to which APAVs are observed prior to SAs. The trading volume estimation is carried out considering all four factors discussed in the previous section. Preliminary, the non-normality of daily trading volume observations is first neutralised by defining the value to be $ln\ (1+Volume_{it})$. The notation V_{it} in Equation (5.26) is used to denote the $ln\ (1+Volume_{it})$, the natural log of firm volume traded on day t. V_{mt} denotes $ln\ (1+Volume_{mt})$, the natural log of the market volume traded on day t; 1 is added to the volume to avoid the issue of log transformation of zero values, (i.e., events of zero volume). Thus, the daily natural log volume for each security i on day t is computed as described by Equation (5.26).

$$V_{i,t} = \alpha_i + \beta_{1i} V_{m,t} + \beta_{2i} TimeTrend + \beta_{3i}\,\mathrm{Sun}_{\,i,t} + \beta_{4i}\,\mathrm{Mon}_{\,i,t} + \beta_{5i}\, Tue_{i,t} + \beta_{6i} Wed_{i,t} + u_{i,t} \tag{5.26}$$

where V_{mt} is the market volume (log scale) traded at time *t*, the variable time trend is included to capture a momentum trend in the behaviour of the stock volume over time, and Sunday to Wednesday are the weekdays dummy variables. The βs are estimated for each event by regressing the stock volume on the index volume, time trend and day-of-the-week dummies in the estimation window.

H_{07} and H_{08}, derived in Section 4.3.6.3, relate to whether an announcement had no significant impact on the distribution of CAVs over the post-event window as per H_{07} and no significant impact on the CAVs during the pre-event window as for H_{08}. To test these hypotheses, a prerequisite step is to estimate the expected trading volumes. This is because the AV is defined for each individual security as the difference between the expected volume $\widehat{E(V_{i,t})}$, predicted by Equation (5.27), and the actual volume $(V_{i,t})$ traded. The trading volume market model shown in Equation (5.26) is used to estimate the expected volume for each security *i* at time *t* by

$$\widehat{E(V_{i,t})} = \hat{\alpha}_i + \hat{\beta}_{1i} V_{m,t} + \hat{\beta}_{2i}\, TimeTrend + \hat{\beta}_{3i}\,\mathrm{Sun}_{\,i,t} + \hat{\beta}_{4i}\,\mathrm{Mon}_{\,i,t} + \hat{\beta}_{5i} Tue_{i,t} + \hat{\beta}_{6i}\, Wed_{i,t} \tag{5.27}$$

The model is based on a trading volume market model regression line using OLS estimation. However, Ajinkya and Jain (1989) point out that although the OLS estimates of the intercept and slope coefficient are unbiased, they are not effective in the presence of serial correlation. These findings are in line with Monteiro et al. (2007) who indicate that OLS estimation is unbiased but not effective in the case of serial correlation. Furthermore, as discussed in the previous section, prior studies on the Tadawul document that it is impacted by seasonal events producing high volatility. Issues of serial correlation and heteroscedasticity would likely impact the estimation of AVs, leading to incorrect inferences about the VMCMs.

Unlike previous studies in the context of market cleanliness trading volume, this study sets out four scenarios to overcome these issues and arrive at more reliable conclusion about AVs as well as more accurate results for the VMCMs. Thus, similar to the procedure employed in the ADL-GARCH approach for the returns analysis, several statistical tests are conducted in hypothesis testing to verify the existence of serial correlation and heteroscedasticity and allow for selection of the most appropriate model. In alignment with the data features, the following four scenarios illuminate the procedures followed to enable unfavourable data features to be identified and treated.

First, if there is no evidence of serial correlation or heteroscedasticity in the volume data, a simple regression of trading volume market model is employed. Second, if the data merely show a variation in variance over time, the estimation of the AV is done by extending the market model according to the GARCH (1,1) process. Third, to control for the presence of serial correlation, the ADL (1,1) model is fitted to estimate AV. Fourth, if both serial correlation and heteroscedasticity are observed, ADL-GARCH is employed. Table 5.5 summarises the four possible scenarios and the corresponding time series models. Table 5.6 presents the null hypotheses and the tests used to select the best model that suits the data features.

Table 5.5

Description of the Scenarios and Corresponding Model Utilised for Each Scenario in Volume Analysis.

Scenario description	Designated model
Neither serial correlation nor heteroscedasticity.	Simple Linear Regression

Presence of only heteroscedasticity.	GARCH (1,1) model
Presence of only serial correlation.	ADL (1,1) model
Presence of both heteroscedasticity and serial correlation.	ADL-GARCH model

Table 5.6

The Null Hypotheses and the Tests Used to Verify the Presence of Heteroscedasticity and Serial Correlation in the Volume Data.

Null Hypothesis	**Tests Name**
H_{07a}:There is no heteroscedasticity.	Engel’s LM-Breusch-Pagan-Godfrey.
H_{07b}:There is no serial correlation.	Durbin Watson, Wald, Chi-Square.

To select the best class of model for each stock data, the tests presented in Table 5.6 are conducted to examine the presence of serial correlation and heteroscedasticity. For each event, the first step is to estimate the series of AVs predicted by the trading volume market model as per Equation (5.27) stated above, using the data from the estimation window. The AVs are computed as the actual volumes traded minus the expected volumes traded for company *i* on day *t*. Thereafter, estimated time series are tested for changes in their serial correlation and variance during the period.

To determine whether the trading volumes exhibit conditional heteroscedasticity, Engle’s LM test is computed to test for ARCH (1) effects. If the test fails to reject null hypothesis H_{07a}, this means that the OLS market model error terms have constant variance. Under the alternative hypothesis, if the test results reveal that the data is not homoscedastic, the null hypothesis is rejected because the data are heteroscedastic as a function of the ARCH (1) effect. As explained earlier, according to the test results, the four scenarios outline the appropriate use of different classes of model utilised for more systematic estimation of the AV.

To check whether the residuals predicted by conventional OLS estimates described in Equation (5.27) are serially correlated, the first procedure is carried out assuming that the residuals are not serially correlated over the trading volumes. To test null hypothesis H_{07b}, that the error term is not serially correlated, the analysis considers the following test statistics; the Durban–Watson and LM tests for statistical computing. If the null hypothesis is not rejected, this implies that there is no serial correlation.

Like in the first scenario, if the statistic tests indicate that the data are homoscedastic and not serially correlated, the trading volume market model according to the OLS estimate, shown in Equation (5.27), is utilised. Then, the $AV_{i,t}$ for firm i on day t is computed as the actual volume traded minus the expected volume traded, as shown by Equation (5.28):

$$AV_{i,t} = V_{i,t} - E\widehat{(V_{i,t})} \qquad (5.28)$$

The discussion now turns to address the second scenario in which the LM test for ARCH effects leads to rejection of the null hypothesis H_{07a} because of the existence of heteroscedasticity, but the Durban–Watson test suggests no presence of seral correlation. The AVs are modelled using Equation (5.27) with recognising that the variance in estimation errors changes over time because of the GARCH (1,1) process. The GARCH model is described by Equation (5.29). Then, the AVs are calculate using Equation (5.28) above.

$$\sigma_{i,t}^2 = \omega_i + \alpha_i u_{i,t-1}^{2} + \beta_i \sigma_{i,t-1}^2 \qquad (5.29)$$

In the third scenario the tests lead to rejection of the null hypothesis H_{07b} revealing only the presence of serial correlation (i.e., the AVs are serially correlated). To address the problem of serial correlation, the AVs are estimated using the ADL (1,1) model shown by Equation (5.30):

$$\begin{aligned} V_{i,t} = \pi_i + \lambda_i V_{m,t} + \gamma_i V_{i,t-1} + \delta_i V_{m,t-1} + \beta_{2i} TimeTrend + \beta_{3i}\, Sun_{\,it} \\ + \beta_{4i}\, Mon_{\,it} + \beta_{5i}\, Tue_{it} + \beta_{6i} Wed_{it} + u_{i,t} \end{aligned} \qquad (5.30)$$

where π_i denotes the intercept of the equation, λ_i refers to the effect of the market volume, γ_i is the effect of lagged firm volume, δ_i is the effect of lagged market volume, β_2 refers to the time trend effect and β_3 to β_6 represent day-of-the-week effects. Equation (5.28) is used to calculate the AVs.

In the fourth scenario where both serial correlation and heteroscedasticity are detected, a consolidation of the ADL model in Equation (5.29) with GARCH Equation (5.30) is employed to treat the joint existence of these issues. Thereafter, the AVs are computed utilising Equation (5.28).

5.7.3 Calculating the Cumulative Abnormal Volume

The previous section presents the models used to accurately estimate AVs. An aggregation of cumulative abnormal volumes (CAVs) is now necessary to draw conclusions about the impact of certain events on the trading volumes. The observations of AVs are aggregated across each individual event to accumulate the AVs over event window observations. By summing CAVs for the period being examined, CAVs can be obtained for each announcement during the post-event window as shown in Equation (5.31) and pre-event window as shown in Equation (5.32):

$$^{(\tau_{-2},\tau_{+2})}CAV_i = \sum_{t=\tau_{-2}}^{\tau_2} AV_{i,t} \tag{5.31}$$

$$^{(\tau_{-2},\tau_{-1})}CAV_i = \sum_{t=\tau_{-2}}^{\tau_{-1}} AV_{i,t} \tag{5.32}$$

There are two windows in which their CAVs are investigated: (i) the CAVs of post-event window; and (ii) the CAVs across pre-event window. The first CAVs, described by Equation (5.31) stands for the total $^5CAV_i$, which denotes all days during the post-event window. The second CAV, described by Equation (5.32) stands for ${}^{-2}CAV_i$, which denotes the CAVs over the pre-event window. In other words, the post-event window ${}^{(-2,+2)}CAV_i$ includes the total CAVs for the five trading days across the event window, including the event day ($\tau = 0$); and the pre-announcement ${}^{(-2,-1)}CAV_i$ is comprised only of the two trading days preceding the day of the announcement, excluding the event day ($\tau = 0$).

To investigate whether there is evidence that the SAs were preceded by APAVs, the bootstrapping technique used in the returns analysis (see Section 5.4.3) is employed on the volumes data. After running the bootstraps for all firm announcements, a statistical hypothesis testing procedure is designed to determine whether there is enough evidence to conclude that there were instances of APAVs detected prior to SAs. Under null hypothesis H_{07}, the CAVs over the post-event window are not affected by the announcement. If the test leads to rejection of the null, the event is classified as a SA.

Having identified SAs, another hypothesis test is performed for H_{08}. Under this null hypothesis the CAVs across the pre-event window are significantly influenced by the event. If the null H_{08} is rejected, this suggests that the event experienced APAVs. In this case, the event is defined as an APAV, which indicates that potential insider trading activities is likely to have occurred.

5.7.4 The Market Cleanliness Measure of Volumes

The analyses described in the previous sections enable identification of the number of events classified as SAs and the number of events for which the APAVs were observed. The volume market cleanliness measures (VMCMs) can now be computed by dividing the total number of APAVs by the total number of SAs as expressed in Equation (5.33):

$$Volume\ Market\ Cleanliness\ Measure = \frac{\sum APAVs}{\sum SAs} \tag{5.33}$$

Having estimated the market cleanliness measure of the trading volume event study during the pre-financial reforms and post-financial reforms, the analysis proceeds to test the second main research hypothesis (i.e., MH_{02}), which states that the difference in VMCMs between the two periods is not statistically significant. To test this hypothesis, the *z*-test shown by Equation (5.10) is performed, considering the findings of the volume analysis. The test assumes that each event in a particular sample has the same probability of being preceded by an APAVs regardless of any other explanatory variables (i.e., the chance of an event occurring is not dependent on another event occurring). If n_1 is the number of observations in set *1*, P_1 is the probability of an event being an APAVs, $Q_1 = 1-P_1$, $n_1 P_1 \geq 5$ and $n_1 Q_1 \geq 5$ where P and $Q = 1-P$ are the average ratios for the two samples.

5.8 Chapter Summary

The data sample, source and period are addressed in this chapter. The chapter describes the selection criteria applied to arrive at a clean sample and justifies the selection of the announcement types. The chapter also describes the structure of the MCMs in the returns and volume event studies conducted for the present research by defining the event window and estimation window, estimating the parameters of the selected models to measure ARs and AVs, and designing the framework for hypothesis testing of the statistical significance of CARs and CAVs. The chapter describes the MM approach used to estimate ARs using the SLR model. It also presents the procedure for the ADL-GARCH approach, which not only demonstrates the ways in which the modelling of ARs and AVs is constructed, but goes on to explain the procedures performed to utilise a suitable model for more systematic estimation. The chapter provides a description of the logistic regression model used to examine if MCMs may be impacted by other factors.

Chapter 6: Empirical Results

6.1 Introduction

The preceding chapter describes the methodologies used to test the research hypotheses. This chapter presents findings from the four empirical analyses conducted in this research. First, the results of the conventional market cleanliness measure for the return event study according to MM approach. Second, the findings of the advanced market cleanliness measure for the return event study according to ADL-GARCH approach. Third, the logistic regression results of the sample-specific effects on the market cleanliness measures. Forth, the outcomes of the market cleanliness measure for the volumes event study. The results reported in this chapter empirically address the following main research questions (MRQs), research questions (RQs) and research sub-questions (RSQs):

RQ_1. Is there evidence of SAs wherein firms announcements have a significant impact on the distribution of cumulative abnormal returns (CARs) during the post-event window?

RQ_2. Is there evidence of APPMs wherein firms announcements have a significant impact on the distribution of CARs over the pre-event window?

RSQ_1. Do the stocks return residuals suffer from the presence of heteroscedasticity and serial correlation?

RQ_3. Does the use of multiple event windows with varying lengths have a statistically significant impact on the results for the MCMs between the two periods?

MRQ_1. Is the level of potential insider trading assessed by the MCMs of returns event study significantly lower after the introduction of financial reforms?

RQ_4. To what extent do sample-specific characteristics of the seven factors examined have an impact on the MCMs?

RQ_5. Is there evidence of SAs wherein firms announcements have a significant impact on the distribution of cumulative abnormal volumes (CAVs) over the post-event window?

RQ_6. Is there evidence of APAVs wherein firms announcements have a significant impact on the distribution of CAVs over the pre-event window?

RSQ_2. Do trading volume data suffer from the existence of heteroscedasticity and serial correlation?

MRQ_2. Is the level of potential insider trading assessed by the MCMs of trading volume event study significantly lower after the introduction of financial reforms?

RQ_7. Is there a relationship between the MCMs of the return and volume analysis wherein the SAs that were accompanied by APPMs were also accompanied by APAVs?

The remainder of this chapter is structured as follows. Section 6.2 presents the empirical results for the MCMs in the returns event study analysis. The section is divided into three parts. Section 6.2.1 presents the results for the MCMs from the MM approach; Section 6.2.2 shows the results obtained from the ADL-GARCH approach; and Section 6.2.3 compares the findings of these approaches to evaluate their efficacy and identify their differences. The logistic regression results for sample-specific effects are presented in Section 6.3. Section 6.4 presents the results for the VMCMs from the volume event study. Section 6.4.1 reports on the findings of the relationship between the return and volume analyses. Section 6.5 summarises the chapter.

6.2 Empirical Results for the Market Cleanliness Measure in the Returns Event Study Analysis

This section addresses RQ_1, RQ_2, RSQ_1, RQ_3, RQ_4 and MRQ_1 based on analysis of (i) the MM approach described in Section 5.4, (ii) the ADL-GARCH approach outlined in

Section 5.5, (iii) and the logistic regression analysis explained in Section 5.6. This section reports the findings for the MM and ADL-GARCH approaches separately and then draws comparisons between them. Both approaches use the same sample to rule out any potential influence of changes in the sample or its size on the MCMs. Table 6.1 provides an overview of the number and type of unscheduled announcements analysed during the relevant period.

Table 6.1

A Detailed Description of the Samples of Unscheduled Announcements Analysed Over the Relevant Period.

Relevant period	**Year**	**No/ year**	**Type of announcements**					
			Acquisition	Takeover	Awarding contract	Merger	Good news	Bad news
Pre-financial reforms	2011	106	12	14	22	3	49	6
	2012	145	13	8	40	6	71	7
	2013	144	10	10	40	9	67	8
	2014	177	19	15	41	7	82	13
	2015	137	16	15	38	0	62	6
	2016	52	4	5	6	0	35	2
Total	1st half	761	74	67	187	25	366	42
Post-financial reforms	2016	173	14	11	63	1	77	7
	2017	262	14	8	76	24	128	12
	2018	288	22	11	89	21	137	8
	2019	351	29	16	86	28	176	16
	2020	123	12	5	17	14	69	6
Total	2nd half	1197	91	51	331	88	587	49

Note: In this table we documented the number of events per year (No/year), the total number of the events analysed during the relevant period. The year starts 26th April and ends 25th April.

6.2.1 Results According to the MM Approach

The empirical findings presented in this section pertain to the results derived from the MM approach. As described in Section 5.4, the MM approach uses a SLR model to estimate securities ARs and infer statistical significance of the CARs using a bootstrap technique (see Section 5.4.3). The existence of statistically significant CARs over the post-event window implies that the announcement contains important news and should be considered a SA and statistically significant CARs across the pre-event window are indicators of the occurrence of APPMs.

Table 6.2 to Table 6.5 present data addressing RQ_1 and RQ_2. The tables provide descriptive statistics of the statistical significance level for the actual CARs calculated over an event window of length (–2, +2) for the sample analysed throughout the relevant period. To examine whether the CARs represent significant price movements, they are compared against the ninetieth percentile threshold of simulated CARs for the empirical ARs distribution generated by the bootstrapping technique for the estimation window. The post-event window CARs are associated with the assessment to determine whether there is sufficient evidence to classify the event as a SA, and the pre-event window CARs are used to make inferences about whether APPMs have taken place ahead of SAs.

The data presented in Table 6.2 and 6.3 relate to the pre-financial reforms period. Table 6.2 shows that there were 24 SAs, but these were not accompanied by APPMs, and Table 6.3 shows that there were 31 SAs preceded by APPMs. This implies a total of 55 SAs over the post-reform period. To explain the tables, the column titled actual post-event CARs shows that the null H_{04}, which states that the event has no significant impact on the distribution of CARs over the post-event window, is not rejected. The actual pre-event CARs column shows results of testing H_{05}, which postulates that the announcement has no significant impact on the distribution of CARs over the pre-event window. The actual pre-event CARs column in Table 6.2 shows no evidence to confirm the null H_{05}. However, Table 6.3 reveals that there were 31 events for which the test fails to reject the null H_{05}. The findings for the post-reforms period indicate that 40 events in Table 6.4 and 33 events in Table 6.5 satisfy the determined statistical threshold for being SAs (i.e., the null H_{04} was rejected). Hence, the total number of SAs detected during the post-reforms period was 73. Table 6.5 indicates 33 instances of APPMs that satisfy the determined statistical threshold for being SAs and preceded by APPMs over the post-reforms period.

Table 6.2

The CARs of the Events Found Statistically Significant to be Classified as SAs, but not Preceded by APPMs During the Pre-reform Period.

No. of Events	**Actual post-event CARs (-2,+2) Sig. at 1%***	Simulated post-event CARs		**Actual pre-event CARs (-2,-1) NS. at 10%*****	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
1	8.64	6.76	-4.20	0.59	2.53	-1.96
2	-9.32	8.49	-7.29	0.64	3.64	-3.12
3	-9.38	8.85	-6.81	-0.66	3.08	-2.61
4	14.93	14.8	-9.48	-2.81	5.99	-4.02
5	10.81	10.35	-6.04	0.75	2.99	-2.68
6	10.11	8.68	-6.02	-1.31	3.35	-2.77
7	-10.96	10.93	-7.61	-1.82	4.33	-3.24
8	-12.20	11.61	-8.62	-0.10	3.45	-3.12
9	-8.43	7.2	-6.43	-0.84	3.02	-2.31
10	-22.30	13.38	-13.20	-3.73	5.2	-4.26
11	5.81	5.34	-5.60	-0.19	1.72	-1.31
12	-4.27	3.69	-3.47	-0.37	1.65	-1.49
13	6.78	5.02	-5.49	2.06	2.32	-2.18
14	-6.24	4.93	-5.61	0.39	2.1	-2.16
15	-9.22	8.79	-6.61	-0.30	2.78	-2.45
16	6.34	5.38	-5.70	-0.29	2.4	-2.07
17	-17.49	12.66	-8.30	0.72	5.38	-3.26
18	11.01	9.09	-7.14	-0.02	2.93	-2.77
19	-5.80	4.34	-3.70	0.22	1.88	-1.63
20	-9.50	9.9	-7.18	3.84	3.93	-2.91
21	7.52	6.98	-7.90	2.09	3	-2.78
22	21.89	14.31	-12.18	0.95	6.1	-3.96
23	8.93	6.42	-5.67	0.26	2.85	-2.36
24	4.95	4.87	-3.48	-0.03	1.87	-1.57

Note: This table shows the events that were determined as SAs, but they were not preceded by APPMs. * Actual post-event CARs (-2,+2) represents the SAs for being higher than or equal to the 0.5% quantile or lower than or equal to the 99.5% quantile. *** The actual pre-event CARs (-2,-1) shows the events, that were not significant (NS), for which the null hypothesis H_{05} was not rejected. They were tested at 10% significance level, but they did not meet our statistical threshold to be considered as APPMs.

Table 6.3

The CARs of the Events Classified as SAs and Preceded by APPMs During the Pre-reform Period.

No. of Events	**Actual post-event CARs (-2,+2) Sig. at 1%***	Simulated post-event CARs		**Actual pre-event CARs (-2,-1) Sig. at 10%****	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
1	23.82	5.32	-10.66	3.78	2.27	-1.75
2	13.53	10.94	-8.88	11.54	4.79	-3.73
3	-87.68	9.57	-6.37	-90.78	3.23	-2.79
4	16.29	9.15	-6.98	11.51	3.91	-3.19
5	16.20	11.69	-7.51	6.14	3.95	-3.14
6	18.81	14.29	-8.82	19.18	5.15	-3.59
7	21.26	11.93	-7.91	11.60	3.30	-3.15
8	11.06	4.63	-7.38	7.46	1.91	-1.75
9	-4.03	4.09	-3.35	-3.94	1.64	-1.45
10	-9.84	11.41	-5.17	-4.77	2.53	-2.32
11	-23.33	8.04	-6.02	-14.70	2.58	-2.33
12	-9.27	6.53	-7.51	-8.35	2.84	-2.67
13	12.17	6.12	-5.81	4.37	2.51	-2.65
14	6.66	6.51	-5.93	3.90	2.79	-2.46
15	6.79	6.60	-5.45	4.72	2.78	-2.36
16	6.32	5.93	-5.17	6.11	2.06	-2.02
17	11.21	8.31	-8.38	6.91	3.25	-3.03
18	-12.13	7.36	-7.53	-4.04	3.21	-2.93
19	4.33	3.97	-3.99	2.14	1.59	-1.60
20	-7.74	8.31	-4.94	-2.26	3.22	-2.26
21	9.13	7.88	-5.68	6.44	3.23	-2.53
22	-8.72	7.75	-7.28	-3.16	2.94	-2.98
23	-9.14	11.79	-8.46	-3.66	4.26	-3.45
24	14.84	13.63	-9.66	10.39	5.00	-4.46
25	12.96	12.45	-7.28	6.66	4.95	-3.37
26	8.36	7.69	-6.34	4.04	3.24	-2.52
27	-16.36	15.64	-12.56	-10.89	7.83	-4.10
28	11.96	6.33	-4.74	3.95	2.35	-2.00
29	-7.86	10.57	-7.38	-5.99	3.93	-3.07
30	-10.12	11.53	-7.90	-4.90	4.66	-3.58
31	-13.84	16.05	-10.94	-9.32	7.27	-4.60

Note: * The actual post-event CARs (-2, +2) refer to the events that were rated as SAs at the significance level of 1% (a two-tailed test). These CARs associated with each event were compared against the 50000 random simulated post-event CARs values generated by bootstrap and were determined to be statistically significant given that they were either higher than or equal to the 0.5% quantile or lower than or equal to the 99.5% quantile. ** The actual pre-event CARs (-2,-1) refer to the events for which the APPMs were detected. These events CARs were compared with the 500 simulated conditional pre-event CARs and considered statistically significant at the 10% level because they were either larger than or equal to the 90% quantile or lower than or equal to the 10% quantile provided that they have the same sign as of the actual post-event CARs from the limited set of 500.

Table 6.4

The CARs of the Events Found Statistically Significant to be Classified as SAs, but Not Preceded by APPMs During the Post-reform Period.

No. of Events	**Actual post-event CARs (-2,+2) Sig. at 1%***	Simulated post-event CARs		**Actual pre-event CARs (-2,-1) NS. at 10%*****	Simulated pre-event CARs	
		0.5% quantile	99.5% quantile		90% quantile	10% quantile
1	13.07	8.37	-7.68	0.82	2.64	-2.85
2	19.52	9.40	-8.70	-0.05	3.65	-3.20
3	-15.15	13.07	-9.44	-3.14	4.69	-3.21
4	10.89	8.03	-6.71	-0.98	3.30	-2.68
5	-11.97	13.70	-9.64	1.27	5.07	-4.06
6	19.78	8.93	-8.34	0.40	3.55	-3.17
7	8.67	5.87	-5.19	-0.19	2.47	-2.28
8	-7.10	6.90	-6.70	0.72	3.04	-3.01
9	7.22	6.09	-5.04	0.88	2.19	-1.94
10	7.45	6.04	-5.78	-0.47	2.41	-2.12
11	-14.16	13.01	-11.09	0.41	4.13	-3.36
12	-13.38	16.48	-12.61	-0.69	6.95	-5.24
13	-13.41	14.68	-12.49	-4.57	5.91	-5.15
14	20.22	12.82	-9.62	1.59	4.77	-3.97
15	22.44	6.17	-7.23	1.93	2.74	-2.76
16	10.88	10.04	-7.31	-0.67	3.99	-3.20
17	13.94	13.16	-9.08	0.03	5.58	-3.64
18	12.93	11.96	-9.11	1.50	4.45	-3.17
19	13.37	7.33	-8.43	0.98	3.29	-2.99
20	5.50	5.24	-4.89	1.64	2.22	-2.17
21	22.05	10.43	-11.52	1.53	4.12	-4.70
22	-10.22	8.18	-7.34	-1.46	3.48	-3.28
23	-15.68	11.20	-8.31	-1.94	4.05	-3.63
24	-10.15	11.26	-8.00	-1.61	4.22	-3.06
25	19.63	8.31	-8.17	1.16	3.34	-3.73
26	-6.18	4.69	-5.63	0.46	2.13	-2.27
27	-7.49	3.60	-4.13	-0.83	1.64	-1.52
28	4.11	3.95	-4.10	0.90	1.55	-1.57
29	-10.10	10.75	-8.19	1.70	4.04	-3.62
30	7.78	7.08	-6.53	0.91	2.86	-2.77
31	-9.36	12.65	-7.74	-3.11	5.15	-3.35
32	-13.52	7.14	-6.09	-1.32	1.70	-2.90
33	20.60	13.51	-11.91	3.88	5.42	-4.28
34	-11.20	10.35	-6.34	-0.43	3.65	-2.74
35	-16.06	12.17	-8.71	-1.35	5.14	-3.89
36	-21.17	13.42	-9.75	-2.27	5.17	-3.97
37	7.93	7.40	-8.83	1.90	2.98	-2.65
38	-8.18	8.90	-3.30	-3.23	3.81	-3.43
39	-13.41	11.22	-9.93	-1.44	3.30	-3.19
40	23.76	10.13	-7.07	3.03	4.31	-3.12

Note: The note shown in the Table 6.2 applies to the analysis results reported in this table.

Table 6.5

The CARs of the Events Classified as SAs and Preceded by APPMs During the Post-reform Period.

No. of Events	Actual post-event CARs (-2,+2) Sig. at 1%*	Simulated post-event CARs		Actual pre-event CARs (-2,-1) Sig. at 10%**	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
1	-9.63	12.95	-8.10	-5.62	5.12	-3.63
2	9.23	6.74	-6.37	3.96	2.91	-2.84
3	24.84	13.30	-9.99	10.18	4.80	-4.36
4	19.50	10.72	-9.08	7.61	4.33	-3.88
5	-12.41	12.73	-8.94	-5.17	5.25	-3.91
6	26.56	12.34	-8.56	6.74	5.00	-3.79
7	-8.73	13.16	-8.00	-4.31	5.11	-3.63
8	9.48	6.97	-11.31	4.23	3.06	-3.70
9	14.46	10.41	-8.71	8.08	3.49	-3.47
10	8.31	7.84	-7.35	5.64	3.22	-2.95
11	18.34	7.04	-8.01	4.40	3.14	-3.11
12	-23.20	6.65	-4.81	-8.29	2.47	-2.15
13	-16.32	13.19	-11.12	-5.77	5.62	-4.33
14	12.92	10.91	-12.11	6.61	3.08	-3.77
15	-8.49	11.41	-8.00	-6.84	3.59	-3.35
16	10.71	9.30	-6.43	5.98	3.02	-2.73
17	-12.47	12.34	-7.87	-6.24	5.36	-3.65
18	7.09	5.66	-9.61	2.82	2.43	-2.70
19	13.31	12.21	-9.44	13.60	4.86	-4.19
20	-8.12	4.60	-4.82	-3.02	1.84	-1.56
21	-9.67	3.86	-4.22	-7.39	1.73	-1.51
22	6.21	6.15	-4.63	2.81	1.51	-1.50
23	11.74	9.03	-7.66	4.50	3.87	-3.12
24	18.03	9.50	-7.96	8.22	3.53	-3.58
25	8.40	7.65	-8.18	7.19	3.50	-3.40
26	-9.66	7.44	-7.54	-8.19	3.06	-2.84
27	16.74	9.68	-7.11	5.78	3.35	-3.16
28	-23.70	8.27	-8.71	-4.26	3.87	-3.54
29	-12.62	16.14	-11.51	-9.27	6.86	-5.03
30	13.22	9.29	-10.18	9.80	4.20	-4.09
31	-14.18	10.33	-8.45	-14.35	4.08	-3.55
32	-9.92	9.06	-8.55	-7.93	3.74	-3.44
33	-12.73	14.02	-11.60	-9.67	4.96	-4.77

Note: The note shown in the Table 6.3 applies to the analysis results presented in this table.

After presenting the evidence of the events for which their CARs met the specified threshold of the significance level, Figure 6.1 and Figure 6.2 attempt to show a comparison of the total number of valid announcements analysed throughout the relevant period and the ratio of SAs that pass the statistical threshold for significance at 1% and are therefore considered SAs according to the MM approach. The comparison helps with understanding of whether the apparent increase in SAs over time may have resulted from an increase in the sample size of events assessed over each period. As shown in Figure 6.1, in 2015, only 2.92% of 137 events were SAs; whereas in 2016 (year ending 25 April), 7.69% of 52 events are deemed SAs.

Figure 6.1 depicts that 7.36% of 761 events are identified as SAs during the pre-reform period, and Figure 6.2 shows that 6.13% of 1,197 events are classified as SAs over the post-reform period. This suggests that despite the increase in the total number of events over the post-reform period compared to the previous period, the ratio of SAs is not correlated with the increase in the sample size of year-on-year events.

Figure 6.1

The Percentage of Significant Announcements Among Total Announcements Over the Pre-reform According to the MM Approach.

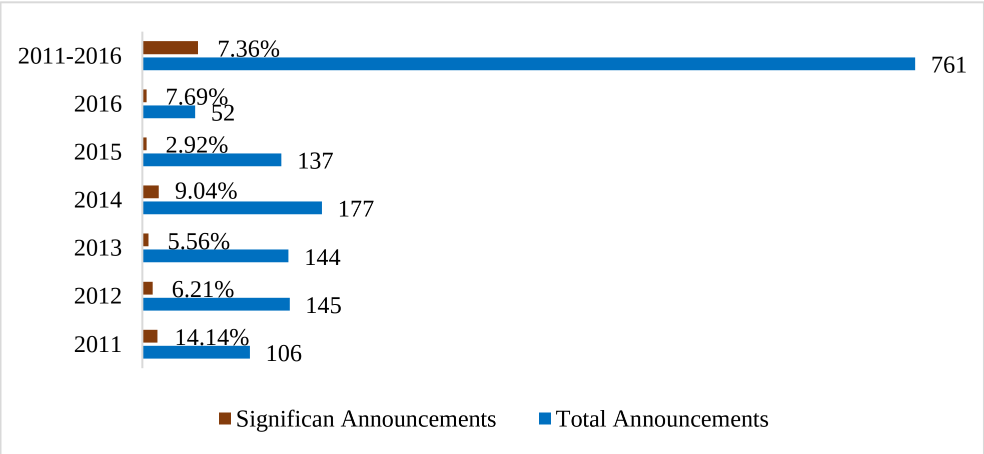
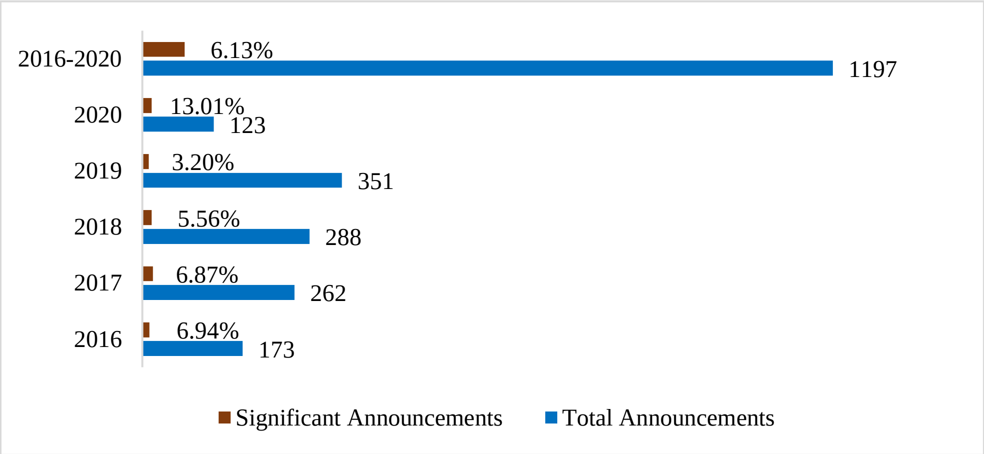


Figure 6.2

The Percentage of Significant Announcements Among Total Announcements Over the Post-reform According to the MM Approach



Before addressing RQ_3 and MRQ_1, it is important to note that the CARs for each event are calculated using different event window settings: (–2, +2), (–5, +5), (–10, +10). As noted above, the evidence regarding the number of SAs and APPMs provided in Table 6.2–6.5 is derived from the analysis using a window of length (–2, +2). However, the total numbers of SAs and APPMs from the other event windows lengths are presented in Table 6.6. In addressing the RQ_3 and MRQ_1, Table 6.6 summarizes the results of the MCMs for the Tadawul before and after the introduction of the financial reforms based on the MM approach, and it includes the total number of original events analysed, events identified as SAs and events for which APPMs are observed. Table 6.6 reports the results across the three event windows settings applied.

Table 6.6

MCMs with Multiple Event Window Lengths According to the MM Approach.

Panel A: Market cleanliness measure during pre-financial reforms period

Event Window Length	**(-2,+2)**	**(-5,+5)**	**(-10,+10)**
Sample*	761	761	761
No. of SA**	55	48	41
No. of APPMs***	31	24	24
MCM****	56.36%	50%	58.53%

Panel B: Market cleanliness measure during post-financial reforms period

Window Length	**(-2,+2)**	**(-5,+5)**	**(-10,+10)**
Sample*	1197	1197	1197
No. of SA**	73	61	57
No. of APPMs***	33	30	32
MCM****	45.20%	49.18%	56.14%

Note: *Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APPMs were observed at a statistical significance level of 10%. **** Market cleanliness measure as the ratio of SAs that were preceded by APPMs.

The results for the MCMs using a five-day event window length (–2, +2), as indicated in Panel A of Table 6.6, show that for 761 announcements, 31 instances of APPMs are detected in advance of a total of 55 SAs, documenting an MCMs value of 56.36% during the pre-reform period. Panel B reports the MCMs for the post-reform period for the same five-day window length, showing that of 1,197 events, 73 are identified as SAs, of which 33 were preceded by APPMs. The data shown in Panel B indicate that the MCMs is 45.20% for the post-reform period, reflecting a drop of 11.16% relative to the previous period.

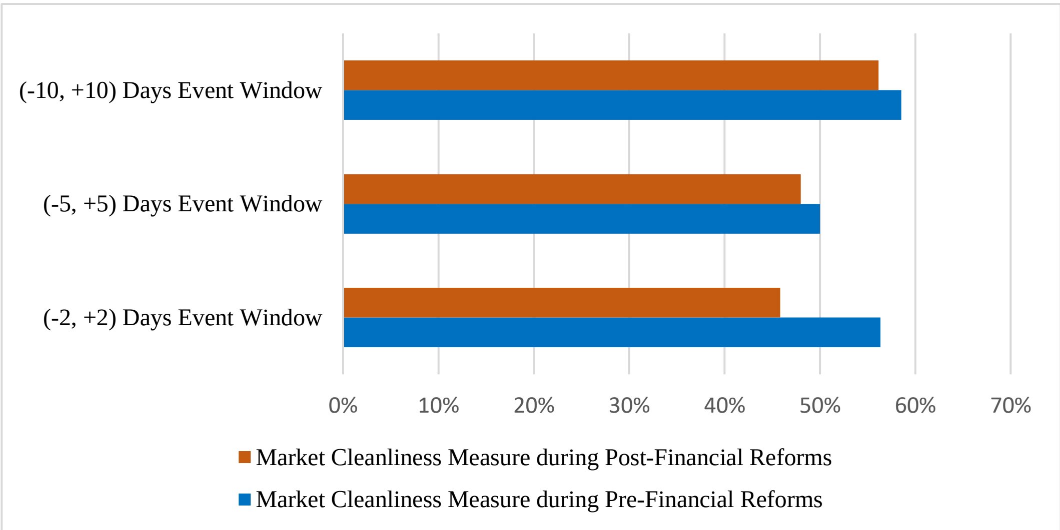
With respect to the findings obtained based on the event window length of 11 days (–5, +5), Panel A shows that the estimated MCMs is 50.00% for the pre-reform period and declined only marginally, to 49.18%, during the subsequent period as shown in Panel B. Panel A shows that 48 of the SAs were preceded by 24 APPM cases over the pre-reform period and Panel B indicates that 61 SAs experienced 30 incidents of APPMs over the post-reform period.

Regarding the results based on the findings derived from an event window of 21 days (–10, +10), Panel A shows that the MCMs over the first half period (58.53%) is 2.39% higher than that in the post-reform period (56.14%), as shown in Panel B. Panel A shows 24 instances of APPMs observed ahead of 41 SAs during the pre-reform period; the equivalent result for the post-reform period (see Panel B) is 57 events identified as SAs, 32 of which exhibited APPMs.

It can be derived from the results presented in Table 6.6 that the MCMs for the post-reform period is lower than that for the pre-reform period for all event window lengths. The results in Figure 6.3 confirm that the measures for the post-reform period is lower than that for the pre-reform period across all event window lengths investigated.

Figure 6.3

The MCMs Calculated for Different Event Window Lengths According to the MM Approach.



To address MRQ_1 and establish the statistical significance of the observed reduction in the MCMs, a statistical test of the difference in the ratio of APPMs between the two periods is performed using a *z*-test computed as:

$$Z = \frac{P_1 - P_2}{\sqrt{PQ(n_1^{-1} + n_2^{-1})}} \qquad 6.1$$

The test assumes that each event in a particular sample has the same probability of being an APPM regardless of any other explanatory variables (i.e., the chance of an event is not dependent on other events). If n_1 is the number of observations in set *1* and P_1 is the probability of an event being an APPM, $Q_1 = 1 – P_1$, $n_1 P_1 \geq 5$ and $n_1 Q_1 \geq 5$ where P and $Q = 1 – P$ are the average ratios for both samples. Table 6.7 presents differences in the MCMs between the pre-and post-reform period for all event window lengths, and accompanying p-values.

Table 6.7

Test Statistics for the Difference in MCMs between Pre- and Post-reforms Periods According to the MM Approach Across all Event Window Lengths.

Panel A: The statistics for event window at length (-2, +2)				
Period	**SAs**	**APPMs**	**Measure**	**Difference**
Pre-financial reforms	55	31	56.36%	11.16% (p-value=0.109)
Post-financial reforms	73	33	45.20%	
Panel B: The statistics for event window at length (-5, +5)				
Period	**SAs**	**APPMs**	**Measure**	**Difference**
Pre-financial reforms	48	24	50%	0.82% (p-value=0.460)
Post-financial reforms	61	30	49.18%	
Panel C: The statistics for event window at length (-10, +10)				
Period	**SAs**	**APPMs**	**Measure**	**Difference**
Pre-financial reforms	41	24	58.53%	2.39% (p-value=0.414)
Post-financial reforms	57	32	56.14%	
Note: The difference in the measure was tested at a 5% significance level.				

Table 6.7 presents the difference in the MCMs between the pre- and post-financial reform periods. The statistical analysis shown in Table 6.7 provides evidence that although

the analysis indicates a drop in the MCMs for the Tadawul after the introduction of financial reforms across all event window lengths, the difference is not statistically significant for any window length examined; thus the null hypothesis is not rejected. It can be seen that the lower level in the MCMs is observed in an event window length of (-2, + 2) shown by a reduction of 11.16% in the MCMs over the post-financial reforms period. Nevertheless, we do not reject the null hypothesis (z = 1.232, p = 0.109) given that the statistic shows that the difference between two periods remains statistically insignificant.

To answer the RQ_3 which pertains to null hypothesis H_{03} which posits that the use of several event windows with varying lengths does not significantly influence the MCMs for the relevant period. The test does not permit the rejection of the null since the difference between both periods was insignificant regardless of the length of the event window used.

Notably, it can be inferred that an event window length of (–2, + 2), which consists of the two days immediately before the event day and two days after, provides the cleanest evidence of potential insider trading activities by capturing the largest number of APPMs. Given that this event widow length has the smallest p-value in favour of the alternative hypothesis among all window lengths, the following presentation of empirical findings primarily focuses on results drawn from the event window of length (–2, +2).

Table 6.8 presents the yearly calculation of the MCMs with an event window length of (–2, +2) including the total number of original events analysed, number of events identified as SAs and number of events for which APPMs are observed. The findings suggest the existence of significant ARs surrounding 128 of 1,958 unscheduled announcements made by firms listed on the Tadawul from 2011 to 2020. Panel A shows that 56.36% of SAs were preceded by APPMs in the pre-reform period compared with only 45.20% in the post-reform period, as shown in Panel B.

Table 6.8

The MCMs Throughout the Relevant Period According to the MM Approach with an Event Window Length of (–2,+2).

Panel A: The measurements during pre-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2011	106	15	9	60%
2012	145	9	8	88.8%
2013	144	7	3	42.8%
2014	177	16	8	50%
2015	137	4	1	25%
2016 (1st half)	52	4	2	50%
2011-2016	761	55	31	56.36%
Panel B: The measurements during post-financial reforms period				
2016 (2nd half)	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2016	173	12	8	66.6%
2017	262	17	7	38.8%
2018	288	16	5	31.2%
2019	351	11	3	27.2%
2020	123	16	10	62.5%
2016-2020	1197	73	33	45.20%

Note: *Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APPMs were observed at a statistical significance level of 10%. ****The ratio of SAs that were preceded by APPMs.

6.2.2 Results From the ADL-GARCH Approach

In the preceding section, RQ_1, RQ_2, RQ_3 and MRQ_1 are addressed in light of the findings obtained from the MM approach. In this section, the same questions are revisited using the empirical findings derived from the ADL-GARCH approach.

To answer RQ_1 and RQ_2 based on the findings of the ADL-GARCH approach, Table 6.9–6.12 report the number of events that have a significant impact on the distribution of CARs over the post- and pre-event windows. The tables present descriptive statistics of the statistical significance level for the actual CARs calculated over an event window of length (−2, +2). To examine whether these CARs comprise significant price movements, they are compared against the ninetieth percentile threshold of the simulated CARs for the empirical ARs distribution for the estimation window period. The actual post-event window CARs are included in the assessment to determine whether there is sufficient evidence to consider the event as a SA, and the actual pre-event window CARs are used to infer whether APPMs took place ahead of SAs.

The data presented in Table 6.9 to Table 6.12 indicate that null hypothesis H_{04}, which posits that an event does not have a significant impact on the distribution of CARs during the post-event window, cannot be rejected. The results reported in column titled actual pre-event CARs in Table 6.9 and Table 6.11 yields evidence to support null hypothesis H_{05} regarding the absence of statistically significant APPMs during the pre-event window. However, Table 6.10 and Table 6.12 presents the data in which that the H_{05} was rejected by showing the number of events that met the established statistical threshold for being SAs and preceded by APPMs in the pre- and post-reform periods, respectively. The data in Table 6.9 and Table 6.10 pertain to the outcomes over the pre-reform period, and findings for the post-reform period are reported in Table 6.11 and Table 6.12.

Table 6.9

The CARs for the Events Found Statistically Significant to be Classified as SAs but Not Preceded by APPMs During the Pre-reform Period According to the ADL-GARCH Approach.

No. of Events	**Actual post-event CARs (-2,+2) Sig. at 1%***	Simulated post-event CARs		**Actual pre-event CARs (-2,-1) NS. at 10%*****	Simulated pre-event CARs	
		0.5% quantile threshold	**99.5% quantile threshold**		**90% quantile threshold**	**10% quantile threshold**
1	23.82	5.42	-10.76	3.78	4.85	-10.68
2	14.34	6.81	-7.71	-1.14	5.91	-7.59
3	6.55	5.55	-5.08	1.62	4.34	-3.80
4	9.34	6.62	-4.40	5.03	5.91	-3.62
5	8.64	6.66	-4.22	0.59	6.07	-3.01
6	-8.65	5.08	-5.76	0.49	4.00	-4.74
7	-9.38	8.95	-6.94	-0.66	8.85	-6.25
8	14.93	14.44	-9.60	-2.81	11.85	-7.87
9	-5.56	7.03	-4.42	-1.79	5.30	-3.84
10	16.20	11.17	-7.62	6.14	10.37	-6.15
11	6.48	5.80	-5.19	-0.35	4.85	-4.10
12	10.81	10.44	-6.08	0.75	10.17	-4.57
13	9.58	6.45	-4.70	-1.40	6.28	-3.19
14	5.96	5.49	-4.86	-1.90	4.06	-3.60
15	-10.96	11.08	-7.61	-1.82	10.10	-6.50
16	-9.73	8.39	-5.60	-0.16	8.35	-5.00
17	-9.48	5.73	-5.43	-0.98	4.42	-4.73

No. of Events	Actual post-event CARs (-2,+2) Sig. at 1%*	Simulated post-event CARs		Actual pre-event CARs (-2,-1) NS. at 10%***	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
18	-11.84	5.12	-7.69	2.99	4.12	-7.69
19	-14.32	6.62	-4.64	-2.40	5.68	-3.74
20	-6.70	6.42	-4.73	0.20	5.67	-4.02
21	-8.19	6.50	-4.59	1.06	5.71	-3.73
22	5.81	5.28	-5.36	-0.19	4.80	-5.25
23	6.66	6.38	-5.90	3.90	5.14	-4.57
24	6.79	6.50	-5.51	4.72	4.97	-4.38
25	-4.39	7.13	-4.12	-2.50	6.55	-3.26
26	-9.27	5.63	-5.01	-0.76	4.22	-3.58
27	-8.67	5.80	-5.45	-1.11	4.88	-4.37
28	6.00	5.19	-5.92	1.91	4.08	-5.78
29	11.21	8.56	-8.16	6.91	7.88	-6.75
30	-12.13	7.08	-7.38	-4.04	5.44	-6.34
31	4.33	3.92	-3.99	2.14	3.29	-3.45
32	6.25	6.18	-4.39	-0.79	5.30	-3.00
33	-6.24	4.90	-5.62	0.39	3.81	-4.82
34	-9.22	9.22	-6.66	-0.30	9.11	-5.97
35	8.65	5.43	-6.50	-0.38	4.01	-6.34
36	-7.67	6.40	-4.54	-1.86	5.41	-3.70
37	-17.49	12.90	-8.37	0.72	12.20	-6.90
38	6.17	5.82	-5.03	1.83	4.78	-3.99
39	-8.72	7.48	-7.46	-3.16	6.14	-6.62
40	-9.14	11.43	-8.20	-3.66	10.56	-6.65
41	10.68	7.44	-5.21	-0.07	7.71	-4.29
42	14.84	13.69	-9.59	10.39	13.34	-7.11
43	-5.80	4.18	-3.75	0.22	3.44	-2.67
44	13.54	8.74	-3.65	6.85	8.17	-3.14
45	-9.50	10.16	-7.10	3.84	8.70	-5.83
46	8.36	7.40	-6.38	4.04	5.80	-5.70
47	-5.21	6.82	-4.61	-3.49	6.18	-3.96
48	7.52	7.17	-7.92	2.09	5.63	-7.85
49	11.96	6.45	-4.82	3.95	5.99	-4.18
50	-7.09	5.91	-5.85	-3.65	5.45	-5.37
51	-10.12	11.30	-7.92	-4.90	10.16	-5.65
52	23.14	5.87	-5.95	0.91	5.28	-5.53
53	10.68	5.77	-5.09	0.30	4.93	-3.88
54	4.95	4.75	-3.49	-0.03	4.17	-2.41

Note: This table shows the events that were determined as SAs, but they were not preceded by APPMs. * Actual post-event CARs (-2,+2) represents the SAs for being higher than or equal to the 0.5% quantile or lower than or equal to the 99.5% quantile. *** The actual pre-event CARs (-2,-1) shows the events, that were not significant (NS), for which the null H_{05} was accepted. They were tested at 10% significance level, but they did not meet our statistical threshold to be considered as APPMs.

Table 6.10

The CARs for the Events Classified as SAs and Preceded by APPMs During the Pre-reform Period According to the ADL-GARCH Approach.

No. of Events	Actual post-event CARs (-2,+2) Sig. at 1%*	Simulated post-event CARs		Actual pre-event CARs (-2,-1) Sig. at 10%**	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
1	13.13	6.71	-4.88	11.16	5.59	-4.11
2	-11.43	6.51	-4.75	-7.22	6.08	-4.37
3	7.25	5.86	-4.90	5.56	4.60	-3.67
4	16.29	9.22	-7.03	11.51	7.68	-5.07
5	-4.37	6.68	-4.02	-4.10	5.38	-2.70
6	18.81	13.81	-8.80	19.18	12.90	-6.55
7	15.81	8.43	-4.04	8.59	8.21	-3.09
8	-9.08	6.04	-5.45	-7.63	5.50	-4.47
9	11.06	4.71	-7.40	7.46	4.17	-7.29
10	-4.03	3.97	-3.39	-3.94	3.49	-2.68
11	-9.84	11.35	-5.40	-4.77	11.46	-4.02
12	-23.33	8.34	-5.86	-14.70	8.16	-5.03
13	-9.27	6.46	-7.34	-8.35	4.99	-6.79
14	15.02	5.58	-5.48	5.39	4.66	-4.43
15	-5.69	6.49	-4.51	-6.34	5.36	-3.45
16	6.32	5.97	-5.30	6.11	6.05	-4.60
17	10.58	6.06	-4.49	7.40	4.73	-3.42
18	-8.29	5.95	-5.06	-10.04	4.88	-4.05
19	7.89	5.82	-4.96	6.19	4.95	-3.75
20	5.11	5.10	-6.44	5.12	3.83	-6.03
21	-7.86	10.71	-7.41	-5.99	8.62	-5.95
22	-6.81	6.71	-4.07	-4.59	5.65	-3.63

Note: * The actual post-event CARs (-2, +2) refer to the events that were rated as SAs at the significance level of 1% (a two-tailed test). These CARs associated with each event were compared against the 50000 random simulated post-event CARs values generated by bootstrap and were determined to be statistically significant given that they were either higher than or equal to the 0.5% quantile or lower than or equal to the 99.5% quantile. ** The actual pre-event CARs (-2,-1) refer to the events for which the APPMs were detected. These events CARs were compared with the 500 simulated conditional pre-event CARs and considered statistically significant at the 10% level, (one-tailed test), because they were either larger than or equal to the 90% quantile or lower than or equal to the 10% quantile provided that they have the same sign as of the actual post-event CARs from the limited set of 500.

Table 6.11

The CARs for the Events Found Statistically Significant to be Classified as SAs, but Not Preceded by APPMs During the Post-reform Period According to the ADL-GARCH Approach.

No. of Events	Actual post-event CARs (-2,+2) Sig. at 1%*	Simulated post-event CARs		Actual pre-event CARs (-2,-1) NS. at 10%***	Simulated pre-event CARs	
		0.5% quantile threshold	**99.5% quantile threshold**		**90% quantile threshold**	**10% quantile threshold**
1	-12.47	12.47	-8.22	-6.24	10.30	-6.34
2	-16.32	13.21	-11.09	-5.77	12.15	-9.92
3	-13.41	14.58	-12.44	-4.57	12.41	-10.59
4	-8.73	12.87	-8.12	-4.31	10.80	-5.80
5	-23.70	8.58	-8.60	-4.26	6.86	-6.88
6	-5.71	5.89	-4.91	-3.16	5.18	-3.79
7	-7.28	5.37	-5.75	-3.15	4.00	-5.42
8	-9.36	12.69	-7.71	-3.11	11.80	-5.73
9	-6.61	5.67	-5.28	-2.98	4.34	-3.87
10	-7.04	6.40	-5.83	-2.80	5.96	-5.43
11	-4.70	6.57	-4.35	-2.58	5.88	-3.26
12	-8.88	6.64	-7.53	-2.39	5.52	-7.49
13	-11.75	8.03	-5.30	-2.28	7.73	-5.16
14	-24.89	4.39	-13.04	-2.10	4.25	-13.12
15	-18.57	6.78	-5.06	-1.97	6.20	-4.30
16	-16.85	5.89	-5.67	-1.74	4.74	-5.53
17	-10.15	11.16	-8.02	-1.61	9.34	-7.78
18	-12.76	6.10	-4.83	-1.52	4.79	-3.72
19	-10.22	5.66	-4.99	-1.51	4.33	-3.76
20	-13.41	11.18	-9.60	-1.44	10.18	-9.61
21	-5.75	5.91	-4.62	-1.36	4.54	-3.29
22	-5.17	6.07	-4.68	-1.30	5.10	-3.45
23	10.89	8.10	-6.86	-0.98	6.52	-5.92
24	7.21	5.49	-5.47	-0.96	4.42	-4.53
25	-10.05	6.96	-4.84	-0.84	5.80	-3.35
26	-5.31	6.34	-4.72	-0.83	5.74	-3.64
27	8.44	6.73	-4.90	-0.75	5.63	-3.97
28	7.59	7.58	-6.89	-0.73	7.04	-5.39
29	-13.38	16.37	-12.56	-0.69	13.48	-9.37
30	10.88	10.08	-7.25	-0.67	9.04	-5.45
31	7.45	6.09	-5.84	-0.47	5.27	-5.52
32	-6.99	6.08	-4.62	-0.39	4.75	-3.60
33	-9.62	7.00	-4.55	-0.20	6.38	-4.05
34	8.67	5.89	-5.19	-0.19	4.81	-3.98
35	7.73	5.80	-5.17	-0.19	4.44	-4.36
36	4.71	4.42	-13.06	-0.18	4.27	-12.97
37	-9.56	7.09	-5.04	-0.17	7.15	-4.57
38	6.57	5.20	-6.50	-0.13	4.28	-5.77
39	17.11	8.29	-10.56	-0.10	7.69	-9.56
40	8.36	7.07	-4.85	-0.01	5.77	-4.13
41	19.59	5.53	-5.54	0.21	4.39	-4.73
42	-11.04	7.07	-5.76	0.23	6.94	-5.17
43	19.78	8.92	-8.19	0.40	8.34	-6.98
44	-6.18	4.82	-5.51	0.46	3.56	-4.65
45	-7.10	6.85	-6.64	0.72	5.28	-4.78

No. of Events	Actual post-event CARs (-2,+2) Sig. at 1%*	Simulated post-event CARs		Actual pre-event CARs (-2,-1) NS. at 10%***	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
46	9.29	5.27	-6.27	0.79	3.92	-5.72
47	13.07	8.33	-7.72	0.82	8.01	-7.21
48	15.52	6.01	-5.40	0.88	5.13	-4.15
49	7.22	6.04	-4.89	0.88	5.44	-4.41
50	8.55	7.28	-4.92	0.90	5.81	-3.68
51	4.11	3.90	-4.10	0.90	3.12	-3.36
52	7.78	7.20	-6.51	0.91	6.48	-5.22
53	-8.75	6.64	-4.66	0.92	5.94	-3.69
54	6.53	6.38	-5.20	0.93	5.59	-4.20
55	-4.95	7.32	-4.81	1.02	6.77	-4.09
56	6.48	5.74	-5.59	1.06	4.55	-4.56
57	7.64	5.89	-5.26	1.11	4.82	-4.33
58	6.54	5.39	-5.61	1.14	4.18	-4.74
59	19.63	8.43	-8.35	1.16	7.16	-6.79
60	9.62	7.02	-4.38	1.19	6.82	-3.72
61	8.54	7.36	-4.76	1.47	6.66	-4.26
62	12.93	12.09	-9.11	1.50	9.97	-8.72
63	17.57	4.99	-5.82	1.52	3.90	-5.17
64	20.22	12.65	-9.44	1.59	11.44	-7.77
65	-10.10	10.27	-8.19	1.70	8.98	-5.95
66	7.93	7.21	-8.66	1.90	6.09	-8.34
67	5.77	5.43	-5.86	2.22	4.28	-5.13
68	7.66	5.29	-5.32	2.28	4.03	-4.29
69	7.44	5.44	-5.37	2.36	4.36	-4.63
70	8.53	5.36	-5.08	2.45	3.92	-3.82
71	5.89	5.55	-5.27	2.64	4.53	-4.11
72	7.31	6.58	-5.41	2.77	6.17	-4.27
73	6.61	5.81	-5.08	2.79	4.86	-4.08
74	7.09	5.67	-9.52	2.82	4.61	-9.52
75	6.47	4.66	-7.45	2.89	3.58	-7.15
76	5.92	5.87	-4.82	2.92	5.05	-3.56
77	6.01	5.61	-5.36	3.06	4.56	-4.40
78	24.05	6.29	-4.43	3.12	5.27	-3.02
79	8.55	6.36	-5.01	3.48	5.86	-4.35
80	5.78	5.58	-4.95	3.78	4.25	-3.72
81	20.60	13.43	-11.96	3.88	11.27	-10.28
82	6.90	5.67	-5.27	3.95	4.45	-3.92
83	9.23	6.90	-6.53	3.96	5.79	-5.24
84	18.34	7.07	-7.95	4.40	5.27	-7.10
85	8.34	5.92	-5.17	4.56	5.98	-3.85
86	-10.23	6.09	-5.29	4.62	5.09	-4.41
87	10.29	8.63	-4.58	4.68	8.63	-3.80
88	6.96	5.71	-5.17	4.70	5.08	-3.99
89	12.66	6.11	-4.51	4.84	4.86	-3.14
90	8.32	6.08	-5.07	5.10	5.46	-3.88
91	12.92	11.17	-11.99	6.61	10.42	-11.60
92	19.50	10.71	-9.02	7.61	9.43	-7.23
93	14.46	11.04	-8.85	8.08	11.15	-7.66

Note: The note shown in the Table 6.9 applies to the analysis results reported in this table.

Table 6.12

The CARs for the Events Classified as SAs and Preceded by APPMs During the Post-reform Period According to the ADL-GARCH Approach.

No. of Events	**Actual post-event CARs Sig. at 1%***	Simulated post-event CARs		**Actual pre-event CARs Sig. at 10%****	Simulated pre-event CARs	
		0.5% quantile threshold	99.5% quantile threshold		90% quantile threshold	10% quantile threshold
1	-20.74	5.96	-5.69	-15.80	4.50	-5.54
2	-14.18	10.31	-8.44	-14.35	8.53	-6.70
3	-23.20	6.78	-4.85	-8.29	6.31	-3.66
4	-9.66	7.36	-7.68	-8.19	6.15	-6.90
5	-6.69	5.85	-5.04	-6.85	4.64	-4.19
6	-8.76	5.52	-5.52	-6.82	4.65	-4.75
7	-9.49	5.86	-5.29	-6.82	5.20	-4.30
8	-7.64	6.40	-5.83	-6.29	5.96	-5.43
9	-6.15	5.64	-5.42	-6.19	4.48	-4.91
10	-8.28	6.71	-4.24	-6.15	5.56	-3.34
11	-7.24	5.89	-4.95	-5.56	4.89	-3.79
12	-13.35	5.94	-4.99	-5.49	4.95	-3.72
13	-6.87	5.73	-5.58	-5.48	4.64	-4.54
14	-4.61	7.30	-4.28	-5.24	6.57	-3.31
15	-13.84	7.34	-5.04	-5.11	7.17	-4.06
16	-7.28	5.89	-5.04	-4.95	5.23	-4.14
17	-6.98	6.54	-4.48	-3.90	6.11	-3.10
18	-4.61	7.10	-4.10	-3.62	6.85	-2.92
19	6.58	5.61	-5.16	4.58	4.41	-3.73
20	11.82	6.54	-4.54	6.53	6.22	-3.08
21	7.90	5.58	-5.50	6.79	4.50	-4.13
22	7.12	5.97	-5.34	7.10	5.00	-4.66
23	15.71	6.45	-4.94	7.14	5.76	-3.69
24	29.20	5.98	-4.90	7.37	4.94	-3.56
25	26.07	5.54	-12.11	7.97	5.11	-12.43
26	19.88	6.17	-5.12	8.11	4.90	-4.29
27	8.38	6.45	-5.01	8.70	6.02	-3.79
28	13.22	9.16	-10.45	9.80	6.91	-8.73
29	7.29	7.06	-4.58	11.70	6.64	-3.68
30	13.31	11.77	-9.62	13.60	10.11	-7.65

Note: The note shown in the Table 6.10 applies to the analysis results presented in this table.

Figure 6.4 and Figure 6.5 compare the overall counts of announcements examined during the relevant period, together with the proportion of SAs that meet the statistical significance threshold of 1% to be classified as SAs using the ADL-GARCH approach. The purpose of the comparison is to determine if an increase in SAs could be attributed to an expansion in the sample size of events evaluated during each respective period.

According to the data presented in Figure 6.4, the year 2014 has the largest sample size, with a total of 177 announcements and ratio of SAs of 11.86%. By contrast, in 2016 (year ending 25 April) the total number of announcements is smaller, at 52, which is a much lower figure compared to that of 2014. It can be noticed that proportion of SAs experienced an increase, reaching 13.46% in 2016. The years 2012 and 2013 have a total of 145 and 144 announcements, respectively, and the percentage of SAs is higher (7.59%) in 2012 than in 2013 (4.86%) even though the total number of original announcements differs by only 1 between these two years.

Regarding the sample for the post-reform period, Figure 6.5 illustrates that the year 2019 has the larger number of events of all years in the sample, with a total of 351 announcements. However, it has the lowest percentage of SAs, at 6.26%. In contrast, the number of events in the year 2020 is 228 fewer than in the previous year although the proportion of SAs linked to the year 2020 is 10% greater than that in 2019.

When comparing the full sample between the two periods (i.e., pre- and post-reforms), although the total sample analysed for the post-reform period is larger than that for the pre-reform period, by 436 events, the difference in the percentage of SAs between the periods is only 0.35%. The results indicate that despite a rise in the overall number of events during the post-reform period compared with the preceding period, there is no discernible relationship between the proportion of SAs and the expansion in the sample size over the two periods, or for year-on-year events. It is worth mentioning that the figures presented here are in consistent with the conclusion from Figure 6.1 and Figure 6.2, presented in Section 6.2.1 regarding the ratio of SAs based on the MM approach.

Figure 6.4

The Percentage of Significant Announcements Among Total Announcements Over the Pre-reform Period According to the ADL-GARCH Approach.

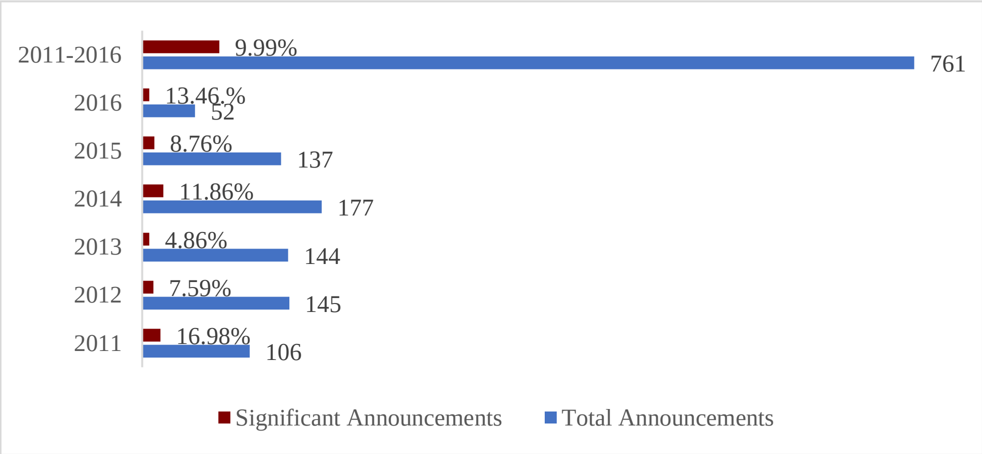


Figure 6.5

The Percentage of Significant Announcements Among Total Announcements over the Post-reform Period According to the ADL-GARCH Approach.

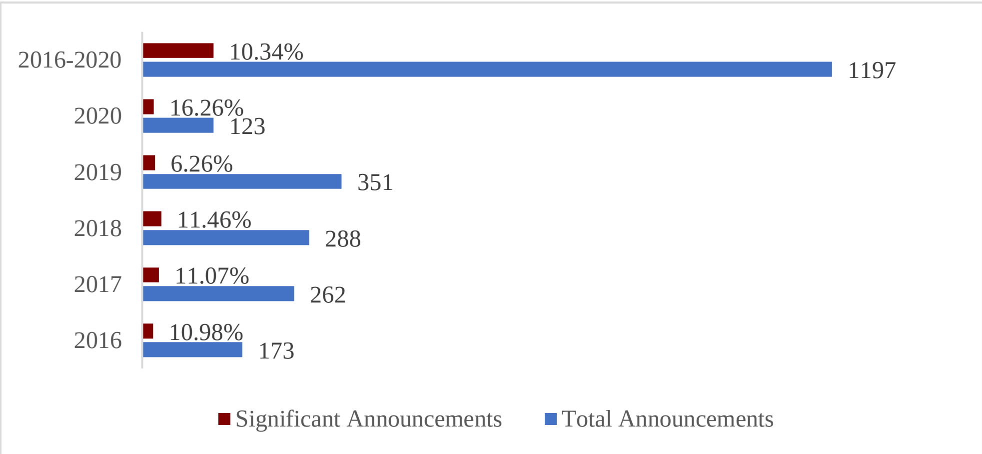


Table 6.13 reports findings for the MCMs of the Tadawul for the periods before and after the introduction of financial reforms according to the ADL-GARCH approach analysis. The table presents data for the overall number of original events analysed, the number of events classified as SAs and number of events in which APPMs were detected. As previously

explained, the computation of CARs uses several event window durations: (–2, +2), (–5, +5) and (–10, +10). Table 6.13 displays the results for each of these event window lengths.

Table 6.13

MCMs with Multiple Event Window Lengths According to the ADL-GARCH approach.

Panel A: Market cleanliness measure during pre-financial reforms period			
Event Window Length	**(-2,+2)**	**(-5,+5)**	**(-10,+10)**
Sample*	761	761	761
No. of SA**	76	75	63
No. of APPMs***	22	23	19
MCM****	28.94%	30.66%	30.15%

Panel B: Market cleanliness measure during post-financial reforms period			
Window Length	**(-2,+2)**	**(-5,+5)**	**(-10,+10)**
Sample*	1197	1197	1197
No. of SA**	123	103	105
No. of APPMs***	30	30	31
MCM****	24.39%	29.12%	29.52%

*Number of original announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APPMs were observed at a statistical significance level of 10%. **** Market cleanliness measure as the ratio of SAs that were preceded by APPMs.

For the five-day event window (–2, +2), Panel A of Table 6.13 shows that a total of 761 announcements are examined for the pre-reform period. Among these, 22 APPMs were detected ahead of 76 SAs, with an MCMs 28.94%. In Panel B, the MCMs for the post-reform period is presented based on the same length of event window, showing a drop in the MCMs by 4.55% compared to the preceding period. Of 1,197 events, 123 are identified as SAs, with 30 of these events being preceded by APPMs.

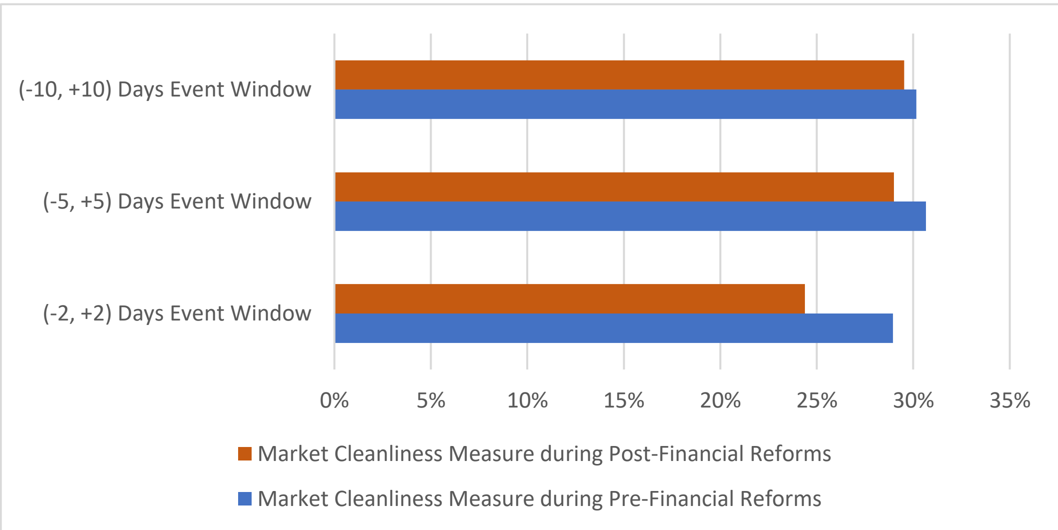
In relation to an event window duration of 11 days (–5, +5), Panel A shows that 75 SAs were preceded by 23 APPMs during the pre-reform period, and Panel B shows that 30 APPMs occurred prior to 103 SAs post-reforms period. Panel A shows that the event window of (–5, +5) has an estimated MCMs of 30.66% during the pre-reform period, and slightly lower, at 29.12%, for the subsequent period as shown in Panel B.

For the analysis using a 21-day event window (–10, +10), Panel A indicates that the MCMs for the first period is 30.15%, which surpasses the measure for the second period by a margin of 0.063%. Based on the data shown in Panel A, APPMs were detected in 19 of the 63 SAs during the pre-reform era. The observations in Panel B indicate that there were 105 events identified as SAs while 31 of them witnessed APPMs incidents over the post-reforms, with an estimated MCMs of 29.52%.

Consistent with the findings presented in Section 6.2.1, Table 6.13 shows that the MCMs for the post-reform period is consistently lower than that estimated for the pre-reform period across all event window durations. These results, as illustrated in Figure 6.6, confirm that the MCMs has witnessed a decline during the post-reform period relative to the pre-reform period across all analysed event window lengths.

Figure 6.6

The MCMs Calculated for Different Event Window Lengths According to the ADL-GARCH Approach.



To address MRQ_1 and determine the statistical significance of the observed decrease in the MCMs based on the results of the ADL-GARCH approach, a statistical test of the difference in the ratio of APPMs between the two periods (i.e., before and after 25 April 2016) is performed using the *z*-test described in Equation (6.1) in the previous subsection. Table 6.14 displays the difference between the MCMs for the periods before and after the introduction of financial reforms and the corresponding *p*-values for all event window sizes tested according to the ADL-GARCH approach.

Table 6.14

The Test Statistics for the Difference in MCMs Between the Pre- and Post-reform Periods According to the ADL-GARCH Across all Event Windows Lengths.

Panel A: The statistics for event window at length (-2, +2)				
Period	**SAs**	**APPMs**	**Measure**	**Difference**
Pre-financial reforms	76	22	28.94%	4.55%
Post-financial reforms	123	30	24.39%	(p-value=0.264)
Panel B: The statistics for event window at length (-5, +5)				
Period	SAs	APPMs	Measure	Difference
Pre-financial reforms	75	23	30.66%	1.54%
Post-financial reforms	103	30	29.12%	(p-value=0.441)
Panel C: The statistics for event window at length (-10, +10)				
Period	**SAs**	**APPMs**	**Measure**	**Difference**
Pre-financial reforms	63	19	30.15%	0.63%
Post-financial reforms	105	31	29.52%	(p-value=0.444)
Note: The difference in the measure was tested at a 5% significance level.				

The statistical analysis presented in Table 6.14 offers supportive evidence indicating that, despite the observed decrease in the MCMs across various event window durations based on the ADL-GARCH approach following the introduction of financial reforms, the null hypothesis cannot be rejected. This conclusion is drawn from the statistics which demonstrate that the decrease over the second half of the relevant period is not statistically significant. A decrease in the measure is evident within the event window of a five-day length (-2, +2) shown by a fall of 4.55% in the MCMs subsequent to the implementation of financial reforms. Nevertheless, we do not reject the null hypothesis (z= 0.629, p-value= 0.264) given that the statistic shows that the difference between two periods is not statistically significant.

To answer the RQ_3 concerned with null hypothesis H_{03}, which proposes that the utilisation of several event windows with different durations has no significant impact on the MCMs. The test results do not provide sufficient evidence to reject the null hypothesis; that is, the observed difference in MCMs between periods is statistically insignificant regardless of the length of the event window. It can be deduced that the event window centred at (–2, +2), encompassing two days immediately prior to the event and two days following it, yields the most reliable evidence of suspicious insider trading activities as it captures more APPMs than other lengths.

Considering the statistical significance of the *p*-value is the smallest for the event window of length (–2, +2) which provides more support for the alternative hypothesis than other lengths windows, the following discussion of the empirical findings thus concentrates on the results for this window length. Table 6.15 presents annual values of the Tadawul's MCMs as determined by the ADL-GARCH method with an event window length of (–2,+2), along with the total number of announcements, SAs and APPMs. The MCMs results in Panel A of Table 6.15 for the pre-reform period show that 28.94% of the SAs experienced APPMs. Panel B of the table indicates that APPMs took place prior to 24.39% of SAs in the post-reform period. The results suggest potential improvement in market integrity of the Tadawul because the level of potential insider trading as measured by the MCMs is 4.55% lower following introduction of the financial reforms. However, the difference between the two periods is not statistically significant (see Table 6.14).

Table 6.15

The MCMs Throughout the Relevant Period According to the ADL-GARCH Approach with an Event Window Length of (–2,+2).

Panel A: The measurements during pre-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2011	106	18	7	38.8%
2012	145	11	4	36.3%
2013	144	7	1	14.2%
2014	177	21	4	19%
2015	137	12	5	41.6%
2016	52	7	1	14.2%
2011-2016	761	76	22	28.94%
Panel B: The measurements during post-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2016	173	19	7	36.8%
2017	262	29	6	20.6%
2018	288	33	7	21.2%
2019	351	22	3	13.6%
2020	123	20	7	35%
2016-2020	1197	123	30	24.39%

*Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APPMs were observed at a statistical significance level of 10%. ****The ratio of SAs that were preceded by APPMs.

The following outcomes pertain to RSQ_1. As explained in Chapter 5, the ADL-GARCH approach is based on four scenarios that outline which model suits the study data to handle the effects of serial correlation and heteroscedasticity. The analysis is carried out for a sample of 1,958 valid announcements of which 761 cover the pre-reform period and 1,197 pertain to the post-reform period. With respect to heteroscedasticity, Engle’s test shows that 37.06% of the pre- and 79.63% of the post-reform events suffer from heteroscedasticity. Regarding the issue of serial correlation, the initial results generated from the Durbin–Watson test indicate that 6.70% of the events experience serial correlation over the pre-reform period and 13.67% for the post-reform period.

However, after correcting for heteroscedasticity by employing the GARCH (1,1), and performing another Engle’s LM test, the figures fall markedly, to 7.75% and 13.27% for the pre- and post-reform periods, respectively. Following serial correlation correction, when employing the ADL (1,1) and then running a second Durbin–Watson test, the results provide no evidence of serial correlation in either period, as the test yields a value of 0%. When using a combination of ADL and GARCH models, serial correlation is found in fewer than 0.66% events in the first period and around 0.79% of the events in the post-reform period sample still exhibit heteroscedasticity. After applying the remedial measures described, the analysis suggests that 697 events (i.e., 91.59%) examined during the pre-reform period and 1,094 events (i.e., 91.40%) assessed during the post-reform period meet the conditions for homoscedasticity and no serial correlation. These results are summarised in Figure 6.7 and Figure 6.8 for the pre- and post-reform periods, respectively.

Figure 6.7

Correction for Serial Correlation and Heteroscedasticity According to Model Selection over the Pre-reform Period.

Scenario	No change		Corrected Serial correlation	Corrected Heteroscedasticity	Corrected Serial correlation & Heteroscedasticity	Total events
No SC & no HK	443					443
Serial correlation only	0		31			31
Heteroscedasticity only	53**			208		261
Serial correlation & Heteroscedasticity	5*	6**			15	26
Total event	507		31	208	15	761

* Stands for the number of events that still exhibit serial correlation.
* * Stands for the number of events that still exhibit heteroscedasticity.

Figure 6.8

Correction for Serial Correlation and Heteroscedasticity According to Model Selection over the Post-reform Period.

Scenario	No change		Corrected Serial correlation	Corrected Heteroscedasticity	Corrected Serial correlation & Heteroscedasticity	Total events
No SC & no HK	540					540
Serial correlation only	0		49			49
Heteroscedasticity only	94**			452		546
Serial correlation & Heteroscedasticity	2*	7**			53	62
Total event	643		49	452	53	1197

* Stands for the number of events that still exhibit serial correlation.
* * Stands for the number of events that still exhibit heteroscedasticity.

6.2.3 Comparison Between the Results from the MM and ADL-GARCH Approaches

This section compares the results for the Tadawul's MCMs obtained using the MM approach presented in Section (6.2.1) and the ADL-GARCH approach reported in Section (6.2.2). Although there are several areas of difference between these two approaches, the conclusions drawn from each notably reinforce each other. The findings concur in terms of the statistical significance of differences in MCMs between the first and second half of the relevant period. Although analyses using both methods indicate a decline in the Tadawul's MCMs over the post-reform period, both approaches consistently show that the observed reduction is not statistically significant. Table 6.16 presents a comprehensive comparison of the Tadawul's MCMs obtained from analysis using the MM and ADL-GARCH approaches for all event window lengths examined.

Table 6.16

A Comparison of MCMs between the MM and ADL-GARCH Approaches across all Event Window Lengths.

	Panel A: The statistics of two approaches according to event window length at (-2, +2)		
Period		MM	ADL-GARCH
Pre-reforms	Sample	761	761
	SAs	55	76
	APPMs	31	22
	MCM	56.36%	28.94%
Post-reforms	Sample	1197	1197
	SAs	73	123
	APPMs	33	30
	MCM	45.20%	24.39%
	Difference	11.16%	4.56%
	Z-test	1.232	0.264
	Panel B: The statistics of two approaches according to event window length at (-5, +5)		
Period		MM	ADL-GARCH
Pre-reforms	Sample	761	761
	SAs	48	75
	APPMs	24	23
	MCM	50%	30.66%
Post-reforms	Sample	1197	1197
	SAs	61	103
	APPMs	30	30
	MCM	49.18%	29.12%
	Difference	0.82%	1.54%
	Z-test	0.1007	0.441
	Panel C: The statistics of two approaches according to event window length at (-10, +10)		
Period		MM	ADL-GARCH
Pre-reforms	Sample	761	761
	SAs	41	63
	APPMs	24	19
	MCM	58.53%	30.15%
Post-reforms	Sample	1197	1197
	SAs	57	105
	APPMs	32	31
	MCM	56.14%	29.52%
	Difference	2.40%	0.63%
	Z-test	0.215	0.444

Note: A statistical test of the difference in the MCMs between two periods (i.e., prior to and following the introduction of financial reforms) was conducted using a z-test.

Broadly, the data presented in Table 6.16 indicate that the MCMs estimated for the Tadawul, are lower with both methods after introduction of the financial reforms. However, all values from the ADL-GARCH approach are lower than their respective values from the MM approach. The ADL-GARCH approach finds fewer instances of APPMs ahead of SAs, appears to be more realistic results which might be attributed to the method employed. This is in line with expectations, as the circularity effect typically leads to overestimation of the detection of APPMs. This is due to the shortcomings of the MM approach, which does not handle the effects of heteroscedasticity and serial correlation of errors assumption. However, by considering these effects, the ADL-GARCH approach remedies the limitations of the MM approach.

To illustrate, the comprehensive survey of the literature presented in Chapter 5 sheds light on potential issues arising from high volatility and autocorrelation that may compromise the accuracy of the traditional event study methodology. Briefly, the market model used in the MM approach operates under the assumption of an OLS estimation, which assumes that the estimation errors of the abnormal returns have the standard statistical properties of a zero expected value and a constant variance that is independent of estimation errors over time. Gujarati and Porter (2009) note that when dealing with time series data for short intervals such as a day or even a few weeks to a month, data observations are subject to sequential movements over the time, and consecutive movements are likely to show autocorrelation. Thus, the assumption of no serial correlation in the error terms under the general condition of OLS assumption is violated.

The explanation of the above statement in the context of MCMs implies that the SAs and APPMs involves an examination of the periods over which the CARs are computed (i.e., the CARs over the post-event window and the CARs across the pre-event window). To examine their significance, the actual CARs of the days that fall within the event window are compared with a sample of simulated CARs drawn randomly from the estimation window using the bootstrap method (see Section 5.4.3). However, the simulation process of randomly drawing returns from the estimation window may yield residuals series that are serially correlated. Thus, the ADL model handles the issue of serial correlation in the residual series.

High volatility would affect the accuracy of the results if there was a significant difference between price volatility during the event window (surrounding the event day) and volatility during the clean period (estimation window). The presence of high volatility during the event window period but low volatility in the clean period may lead to misidentification of events as APPMs. However, the GARCH (1,1) process considers that the variance in the error on a certain day is not constant but rather varies depending on the magnitude of the error term and its variance on the preceding day. The model not only computes single-day ARs; it also considers their variances using returns for a subset of the data from the estimation window period.

The empirical findings from the ADL-GARCH approach are supportive of the interpretation discussed so far. Based on Figure 6.7 and 6.8 (see Section 6.2.2), the ADL-GARCH approach demonstrates superior capability in accurately modelling stock behaviour in 41.3% of 1,958 valid announcements. In contrast, of all the time series estimated using the MM approach, 56.6% exhibited either heteroscedasticity, serial correlation or both. With the ADL-GARCH approach, the percentage decreased to 2.06%. Thus, the inferences derived from the ADL-GARCH approach are more precise and reliable.

It is evident that the event window that encompasses a period of two days preceding and two days succeeding the event day provides the most dependable evidence of potential insider trading activity with both approaches compared with the alternative window lengths of (–5, +5) and (–10, +10). The results from the MM approach based on the event window length of (–2, +2) to some extent suggest that the Tadawul is cleaner than is evident from the

ADL-GARCH approach results while the former represent the largest difference in MCMs between the first and second halves of the relevant period and has the smallest *p*-value ($z = 1.232$, $p = 0.109$). Nonetheless, the difference is not statistically significant for either approach. Having compared the results from the two approaches employed, the following section proceeds to present a further robustness check to enable more meaningful conclusions to be drawn.

6.3 Logistic Regression for the Analysis of Sample Characteristic Effects

Sections 6.2.1 and 6.2.2 report the outcomes for the Tadawul's MCMs along with the conclusions drawn, by estimating the *z*-statistic for the difference between the MCMs before and after the introduction of financial reforms. Although the findings from both the MM and ADL-GARCH approaches notably support each other confirming that the MCMs remains statistically insignificant even when considering the possible effects of event window length and undesirable data features by utilising advanced methods. However, the *z*-test was conducted without considering the potential impact of any sample characteristic effects. Therefore, this section applies a further robustness check by conducting an additional econometric analysis to examine the extent to which differences in the MCMs may be driven by other factors.

Monterio (2007) notes that MCMs may be influenced by sample characteristic effects. For example, changes in samples between periods may affect the MCMs without any underlying change in the level of potential insider trading (i.e., APPMs). Moreover, if one year in the sample is characterised by a higher number of SAs among larger and more liquid firms, this might suggest an improvement in the overall MCMs. This is because some trading activities may not have a substantial price impact. Section 4.1.3 points out several forms of strategy used by insider traders to mask their activities and avoid causing significant impact on the price movements. Moreover, some categories of announcement, as well as announcements issued by companies operating in particular sectors, may exhibit varying degrees of susceptibility to insider trading and information leakages. Taking these into consideration might direct attention towards the different likelihoods of SAs being preceded by APPMs because of sample characteristic effects.

Therefore, to derive more meaningful conclusions about differences in MCMs over the relevant period, the seven factors discussed in Chapter 4 are examined to control for potential sample-specific effects. The goal of this analysis is to investigate whether variation in sample-specific effects may influence the MCMs. The factors that may induce sample-specific effects are firm size, stock volatility, stock liquidity, information asymmetry, the actual size of the CARs over the event window, trading activity and industry variables. With the exception of information asymmetry and trading activity, Monterio (2007) and Dubow (2006) examine these factors, in addition to firm innovativeness. However, the present study excludes the latter factor because of the lack of data pertaining to this particular factor within the firms listed in the Tadawul.

As discussed above, conclusions drawn based on the *z*-test for differences in the MCMs estimated by the MM and ADL-GARCH approaches do not consider the mentioned factors. Thus, dummy periods for the second half of the relevant period are also included in the logit model to assess the statistical significance of the difference between the two periods after controlling for other variables. In order to address this objective and ascertain if the MCMs were not affected by potential sample specific-effects, the null hypothesis H_{06} developed in Chapter 4 was tested by using the logistic regression model.[45] While the model specifications are expressed in Equation (5.25) in Chapter 5, it is useful to restate them for the purpose of explanation by

[45] Chapter 4 discussed the underlying motivations for undertaking this investigation.

$$Logit\ (P_{APPM}) = log\ \left(\frac{P_{APPM}}{1 - P_{APPM}}\right)$$

$$= \alpha_0 + \beta_1\ \textit{firm size} + \beta_2\ \textit{liquidity} + \beta_3\ \textit{volatility} + \beta_4\ \textit{absolute mean post-CAR} + \beta_5\ \textit{information asymmetry} + \beta_6\ \textit{trading activity} + \beta_7\ \textit{Industry} + \beta_8\ \textit{2016 dummy}$$

The dependent variable in the above equation, $log\ (P_{APPM}\ /\ (1\text{-}P_{APPM}))$ (i.e., 1 for APPMs; 0 for non-occurrence of APPMs) denotes the log of the odds ratio for the probability that APPMs have occurred to the probability that they have not. It is computed as the logged odds ratio of P_{APPM} to $1–P_{APPM}$. An odds ratio of 1 implies equal probability of occurrence of an APPM and non-occurrence. If the odds ratio is greater than 1, this suggests that an APPM is more likely to have occurred. In contrast, if the odds ratio is less than 1, this indicates that an APPM was less likely. Two types of independent variable are included. First, the sample-specific characteristics (the seven factors mentioned above). Second, a period dummy for 2016 to examine the difference in the MCMs between the pre- and post-financial reforms periods. A statistically significant negative coefficient would suggest that the level of potential insider trading declined after the financial reforms were implemented, whereas a statistically significant positive coefficient would indicate the opposite. Table 6.17 provides descriptive statistics for the sample-specific factors, and Table 6.18 presents the regression results for the sample-specific effects according to a logit model.

Table 6.17

Descriptive Statistics for the Sample-Specific Factors of SAs and APPMs Over the Relevant Period.

Factors	Median	Mean
Firm size	2305,000,000	2214,0000,000
Stock Liquidity	0.0045556	0.0232166
Volatility	1.7733	1.8333
Absolute post-CARs	13.773	17.05
Information asymmetry	0.0015157	0.0076205
Trading activity	681,701	2,581,018

Note: The data presented in the table is relevant to the sample of the announcements that were classified as SAs and preceded by APPMs. Trading activity refers to average daily traded volume over pre-event window in thousand Saudi Riyal (SAR). The prevailing exchange rate between the USD and the SAR is roughly 3.75.

Table 6.18

Logistic Regression Results for Sample-specific Effects on the MCMs Over the Relevant Period.

Explanatory variables	Logit Coefficients	Std. Error	P value
Firm size	-0.03177	0.19945	0.8734
Stock liquidity	-0.03993	0.24191	0.8689
Stock volatility	-0.05236	0.29194	0.8577
Absolute post-CARs	0.39209	0.35311	0.2668
Information asymmetry	0.08468	0.09605	0.3780
Trading activity	0.48453	0.22292	0.0297 *
Dummy-period	0.23389	0.39761	0.5564
Sector group 1	-0.85646	0.72248	0.2358
Sector group 2	0.411328	0.627384	0.5121
Sector group 3	0.105562	0.639479	0.8689
Sector group 4	1.186916	0.79831	0.1371
Sector group 5	-0.001494	0.75118	0.9984
Sector group 6	-0.240008	0.905099	0.7909
Sector group 7	-0.330848	0.804503	0.6809
Sector group 8	-0.682956	0.690598	0.3227

Note: All the variables are measured using log scale. Hence, the logit coefficients can be interpreted as a percentage change in the odds of APPMs corresponding to 1% increase in each predicator controlling for the remaining explanatory variables. * Statistically significant at 5%. Sectors groups refer to the sectors for which made announcements included in the study sample. Kindly, note, that analysis is limited to those events that were found SAs or APPMs not the other events that were clean. So, this interprets that we have 8 sectors. The sectors groups 1 to 8 stand for Materials, Retailing, Telecommunication, Consumer Durables and Services, Food Staples and Beverages, Health Care Equipment Svc, Diversified Financials and Banks, Real Estate Management and development, respectively.

The regression findings presented in Table 6.18 indicate that, with exception to trading activity factor, none of the other explanatory variables had a significant impact on the probabilities in favour of an APPM. Only trading activity had a significant effect (at the 5% level) on the probability of an APPM occurring. The explanation for this, it is possible to observe that the occurrences of APPMs may often be accompanied by an increase in trading volume surrounding the announcements days. Further interpretations are discussed in more depth in Chapter 7 (see section 7.2.3). A trading volume event study is also performed in the current study, which supports the price analysis and provides evidence of the occurrence of AVs surrounding announcement days.

While Table 6.18 presents the overall results for the factor effects on the MCMs using all data from both periods (i.e., pre- and post-reform), a further analysis is carried out by running the model separately for the pre-reform and post-reform data, to determine if there is a significant impact of particular factors on the MCMs when using the data for each period individually. Table 6.19 reports the results, which are consistent with conclusions based on the logistic regression conducted using the full sample of the relevant period.

Table 6.19

Comparison of Logistic Regression Results for Sample-specific Effects on the MCMs for the Pre-reform and Post-reform Periods.

Factors	**Model results for the data over the pre-reforms**		**Model results for the data over post-reforms**	
	Logit Coefficients	**P-value**	**Logit Coefficients**	**P-value**
Firm size	-0.203 [0.277]	0.464	-0.211 [0.345]	0.541
Stock liquidity	-0.063 [0.319]	0.842	-0.312 [0.420]	0.457
Stock volatility	0.605 [0.500]	0.226	-0.446 [0.546]	0.414
Absolute post-CARs	0.656 [0.541]	0.225	0.530 [0.614]	0.388
Information asymmetry	0.198 [0.178]	0.266	0.160 [0.143]	0.263
Trading activity	0.309 [0.295]	0.295	0.813 [0.351]	0.0206*
Industry group 1	-0.303 [0.968]	0.754	1.070 [0.854]	0.210
Industry group 2	0.332 [0.837]	0.691	1.053 [1.261]	0.403
Industry group 4	1.809 [1.365]	0.185	1.039 [1.114]	0.350

Industry group 5	-2.355 [1.324]	0.075	2.046 [1.017]	0.124
Industry group 6	0.967 [1.034]	0.349	1.148 [1.045]	0.991
Industry group 7	-1.730 [1.195]	0.147	-0.860 [1.175]	0.464
Industry group 8	-0.442 [1.056]	0.675	-2.113 [1.029]	0.444

Table 6.19 presents the results for sample-specific effects on the MCMs by examining the relevant data for each period separately. Analysis of the pre-reform data suggests that trading activity has a positive effect but is insignificant. A positive effect is also seen during the post-reform period, but it is statistically significant at 5%. In a supplementary analysis, an alternative logistic regression model is run, incorporating the period dummy variable and excluding all other variables. The Akaike information criterion (AIC) is 247.91 and 253.99 for the model with and without controllable variables, respectively. It is evident that the difference between the models is insignificant; that is, the likelihood ratio (LR) statistics are 0.055 for the model with all factors and 0.473 for the model with only the dummy period. The quadratic probability scores (QPS) are 0.4277567 and 0.3855822, respectively.

The results obtained from the logistic regression model are consistent with the *z*-test-based conclusion that the MH_{01} cannot be rejected. As shown in Table 6.20, the statistics indicate that the post-reform dummy period does not exhibit statistical significance. The absence of a significant influence of sample-specific factors on the MCMs suggests that the differences observed in the MCMs may be attributable to modifications in regulatory policies rather than the examined sample characteristics.

Table 6.20

Regression Results of the Difference in the MCMs after Post-Reforms Period.

Factor	**Logit Coefficients**	**Std. Error**	**P value**
Dummy Period (post-financial reforms)	-0.2206	0.3073	0.4728 (z-statistic: 0.718)

6.4 Empirical Results for the Market Cleanliness Measures in the Volume Event Study Analysis

Section 6.2 reports the results for the MCMs of the Tadawul based on the returns event study analysis. This section presents empirical findings on the volumes market cleanliness measures VMCMs conducted to examine the extent to which abnormal pre-announcement volumes (APPVs) are detected prior to significant announcements (SAs).

The sample of firms announcements described in Table 6.1 is the same as that used in the analysis of trading volumes. Further, the analysis of trading volume is broadly similar to the returns analysis; nonetheless, it is subject to two limitations. First, the cumulative abnormal volumes (CAVs) are calculated using a single event window length consisting of five trading days (–2, +2). Second, the potential impact of sample-specific effects is not investigated in the volume analysis. Having provided an introductory of the VMCMs, the relevant findings are now presented.

Tables 6.21 to 6.24 address RQ_5 and RQ_6 by presenting empirical evidence regarding events that have a significant impact on the distribution of the CAVs during the post-event windows in the relevant period. The findings imply the presence of significant AVs surrounding 374 of 1,958 unscheduled announcements issued by companies listed on the Tadawul between 2011 and 2020. The tables present descriptive statistics pertaining to the statistical significance level associated with the actual CAVs calculated over the event window spanning from –2 to +2.

To assess the significance of trading volume performance, the CAVs associated with each event were compared to the ninetieth percentile threshold of the simulated CAVs derived from the empirical AVs distribution of the estimation window period. The post-event window CAVs are utilised in the evaluation process to ascertain whether there is sufficient evidence to categorise the event as a SA. The actual pre-event window CAVs are examined to draw conclusions regarding the occurrence of APAVs prior to the release of SAs.

Table 6.21 to 6.24 report the number of events over the relevant period in which the null H_{07}, which states that the event does not have significant effect on the distribution of CAVs during the post-event window, is rejected. Table 6.21 and Table 6.23 report data in which the analysis fails to reject null H_{07} and H_{08} by presenting the count of the events that satisfy the statistical threshold for being SAs and were preceded by APAVs during the periods before and after the introduction of financial reforms, respectively. The column titled actual pre-event CAVs in Table 6.22 and 6.24 present the count of events in which the analysis does not yield any evidence in support of null H_{08} regarding the presence of statistically significant APAVs. Table 6.21 and Table 6.22 presents the data pertaining to the outcomes obtained in the periods preceding the implementation of financial reforms, and Table 6.23 and Table 6.24 report findings for the period following introduction of financial reforms.

Table 6.21

The CAVs of Events Classified as SAs and Preceded by APAVs During the Pre-reform Period.

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
1	4.27	14.55	3.21	5.29	33	6.25	25.44	4.93	21.82
2	4.94	17.18	4.11	10.24	34	4.67	6.62	3.61	3.98
3	4.85	7.86	4.04	4.42	35	5.10	8.10	4.27	5.57
4	5.31	13.38	4.75	6.46	36	4.48	9.24	3.43	4.51
5	6.48	7.94	4.60	7.97	37	4.49	14.04	3.48	6.95
6	4.82	8.30	3.73	5.41	38	4.42	5.38	3.13	3.42
7	5.16	5.76	4.11	4.94	39	5.02	10.21	4.37	5.92
8	4.24	22.60	3.30	10.76	40	4.66	5.74	4.14	4.40
9	5.09	5.80	3.99	4.21	41	4.68	9.73	3.49	3.81
10	4.81	6.87	3.72	3.97	42	4.59	7.46	3.44	3.85
11	4.88	10.32	3.86	5.83	43	4.84	6.70	3.75	4.74
12	5.13	5.57	4.02	4.70	44	5.05	9.05	4.92	5.15
13	5.10	21.03	4.34	8.83	45	6.91	8.62	5.51	26.64
14	4.71	8.27	3.63	4.07	46	4.77	6.33	3.84	4.46
15	5.10	11.24	4.18	4.99	47	4.44	6.71	3.31	3.56
16	4.93	7.36	3.08	3.90	48	4.66	7.78	3.63	5.83
17	4.79	8.07	3.74	4.55	49	6.78	20.13	5.64	11.63
18	5.39	13.55	4.85	6.04	50	5.16	10.50	4.45	4.86
19	5.33	12.62	4.24	7.13	51	4.74	7.40	3.64	3.88
20	5.11	82.83	4.36	62.72	52	6.69	25.41	5.43	11.38
21	5.02	8.43	4.22	5.03	53	5.50	12.55	4.90	7.19
22	6.79	30.01	5.61	14.71	54	6.53	8.41	4.93	6.27
23	6.92	54.51	5.64	26.05	55	5.11	7.47	3.37	7.90

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
24	4.55	10.10	3.50	5.06	56	5.02	11.58	4.70	7.36
25	5.11	12.45	4.15	6.92	57	4.84	10.46	3.81	5.91
26	5.08	8.90	3.99	5.72	58	5.08	11.01	4.45	4.91
27	4.58	11.88	3.57	6.94	59	6.69	8.86	5.18	7.96
28	4.67	6.49	3.55	4.91	60	5.10	8.00	4.41	6.59
29	4.64	7.84	3.80	4.30	61	5.06	10.12	4.29	6.96
30	4.93	7.13	4.11	4.54	62	6.88	16.67	5.56	16.15
31	4.67	6.91	3.45	3.82	63	4.51	9.69	3.31	6.15
32	3.98	6.22	2.87	5.19					

Note: * The actual post-event CAVs (-2, +2) refer to the events that were rated as SAs at the significance level of 1% (one tailed test). These CAVs associated with each event were compared against the 50000 random simulated post-event CAVs values generated by bootstrap and were determined to be statistically significant given that they were higher than or equal to the 99% quantile. ** The actual pre-event CAVs (-2,-1) refer to the events for which the APAVs were detected. These events CAVs were compared with the simulated conditional pre-event CAVs and considered statistically significant at the 10% level because they were larger than or equal to the 90% quantile provided that they have the same sign as of the actual post-event CAVs.

Table 6.22

The CAVs of Events Found Statistically Significant to be Classified as SAs, but Not Preceded by APAVs During the Pre-reform Period.

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
1	5.32	5.40	4.88	1.17	47	5.16	6.82	4.38	3.42
2	5.22	9.88	4.56	4.13	48	5.21	7.17	4.45	3.31
3	5.22	6.85	4.59	2.57	49	4.75	6.65	3.80	3.46
4	5.33	9.83	4.60	3.39	50	6.25	7.11	6.43	4.09
5	5.24	10.34	4.51	4.46	51	4.94	5.63	4.06	3.16
6	5.05	6.28	4.52	0.51	52	4.81	5.36	3.68	1.66
7	4.62	5.82	3.60	2.44	53	4.96	7.48	3.82	0.81
8	4.78	4.89	3.76	3.71	54	5.09	5.59	3.88	2.43
9	4.22	4.48	3.88	0.39	55	4.83	6.24	3.84	2.54
10	5.26	9.89	4.24	4.14	56	4.87	10.29	3.79	2.09
11	4.45	5.54	3.47	1.19	57	4.77	5.54	3.63	2.55
12	5.09	5.59	4.06	3.10	58	5.04	8.74	4.06	2.29
13	7.44	43.14	6.43	3.48	59	5.11	6.01	4.33	2.74
14	5.12	5.24	3.91	3.48	60	5.55	5.66	4.95	2.49
15	5.26	5.38	4.67	2.40	61	5.12	7.20	4.30	3.63
16	4.92	6.50	3.89	3.62	62	4.74	5.75	3.58	1.47
17	5.57	9.14	4.67	3.96	63	4.72	6.54	3.66	3.40
18	4.88	7.34	3.67	2.22	64	5.14	5.22	4.13	0.87
19	5.36	7.00	4.59	2.30	65	4.74	6.29	3.59	1.79
20	5.06	7.93	4.51	3.11	66	4.64	8.09	3.73	0.64
21	5.01	12.84	3.75	3.75	67	5.00	5.66	3.90	2.71
22	5.34	6.16	4.71	3.02	68	5.08	5.33	4.07	1.18
23	5.16	6.94	4.33	3.57	69	4.62	5.49	3.58	3.04

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
24	6.86	10.09	5.32	3.74	70	7.03	14.86	5.42	4.45
25	5.04	6.01	4.44	2.84	71	6.75	13.14	5.13	4.61
26	2.96	3.03	2.27	0.68	72	4.64	5.28	3.59	2.21
27	4.99	6.03	3.94	1.78	73	5.23	5.30	4.63	0.31
28	4.93	8.13	3.87	3.42	74	5.10	6.89	4.06	3.58
29	4.77	5.70	3.76	2.23	75	4.64	5.63	3.50	1.06
30	4.85	6.53	3.94	1.41	76	4.64	8.45	3.86	2.96
31	5.17	6.18	4.06	1.89	77	6.88	9.12	5.61	0.88
32	5.04	9.00	4.16	3.62	78	5.39	7.72	4.46	3.79
33	4.62	8.71	3.90	3.82	79	4.68	6.79	3.52	2.77
34	4.96	13.05	4.02	3.63	80	5.01	5.21	4.41	2.62
35	5.08	5.18	4.00	2.10	81	5.13	5.52	4.00	2.67
36	4.77	15.32	3.73	3.58	82	5.29	8.20	5.02	1.77
37	4.58	5.24	3.81	2.55	83	5.12	7.36	4.29	2.78
38	4.85	5.14	3.77	0.65	84	4.86	6.79	3.96	3.51
39	6.55	13.32	5.12	1.65	85	4.60	4.61	3.46	2.17
40	4.90	5.95	4.25	3.02	86	4.99	5.12	4.23	2.37
41	4.98	6.86	3.88	2.04	87	4.75	6.98	3.66	1.90
42	4.59	6.56	3.46	0.36	88	5.13	5.38	4.82	1.92
43	5.08	9.12	4.62	3.76	89	4.75	9.53	3.95	1.55
44	5.10	5.47	4.29	1.25	90	5.20	6.61	4.52	3.39
45	5.71	5.79	5.80	1.89	91	6.90	12.74	5.40	4.90
46	4.81	5.23	3.67	2.29	92	3.22	4.84	2.53	2.35

Note: This table shows the events that satisfy the determined threshold for being SAs, but they were not preceded by APAVs. * Actual post-event CAVs (-2,+2) represents the SAs for being higher than or equal to the 1% quantile threshold. ** The actual pre-event CAVs (-2,-1) shows the events, that were not significant (NS), for which the null H_{08} concerned with absence of APAVs was not rejected. They were tested at 10% significance level, but they did not meet our statistical threshold to be considered as APAVs.

Table 6.23

The CAVs of Events Classified as SAs and Preceded by APAVs During the Post-reform Period.

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
1	5.08	9.89	4.50	7.61	38	5.27	10.86	4.62	6.40
2	5.27	10.47	5.31	9.34	39	4.74	16.84	4.09	15.47
3	5.15	19.83	5.03	9.02	40	4.49	7.71	3.82	4.56
4	4.78	11.62	4.51	5.31	41	6.90	29.46	6.55	16.35
5	5.00	10.91	4.92	9.22	42	5.19	12.12	4.71	5.73
6	7.49	40.67	7.10	19.98	43	4.89	7.91	4.44	6.33
7	4.58	5.01	3.73	4.74	44	4.87	7.91	4.02	4.61
8	5.17	10.09	4.50	5.97	45	7.02	28.93	6.62	27.72
9	7.37	43.19	8.33	33.51	46	4.86	10.24	4.26	6.61
10	6.62	26.52	5.56	7.18	47	4.74	11.69	4.46	6.43
11	5.16	10.61	4.91	6.36	48	5.14	11.50	5.06	6.42
12	4.61	12.34	3.84	5.58	49	5.15	12.39	5.62	6.70
13	4.65	10.43	3.87	5.66	50	4.49	9.48	3.82	7.60
14	5.21	11.41	5.00	8.03	51	6.59	58.25	5.48	22.90
15	4.91	17.44	4.52	7.30	52	6.82	35.83	6.38	17.98
16	5.18	23.75	4.54	8.41	53	6.49	32.12	5.31	18.27
17	6.90	36.78	6.26	24.45	54	4.28	9.94	3.67	5.63
18	4.33	11.50	3.85	5.25	55	7.54	38.69	7.45	19.79
19	4.72	17.38	4.58	9.03	56	6.76	21.37	6.37	7.64
20	5.04	6.84	4.50	4.99	57	4.54	10.80	4.11	6.22
21	5.06	11.38	4.86	7.71	58	4.37	6.63	4.07	4.60
22	6.36	25.74	5.62	13.46	59	4.92	48.90	4.37	25.58
23	4.67	8.64	4.05	4.71	60	5.07	36.17	4.88	19.10

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
24	4.81	26.25	4.32	8.29	61	4.02	7.84	3.46	3.98
25	3.89	7.43	3.06	5.01	62	4.98	40.15	4.57	19.07
26	4.81	11.29	4.39	7.55	63	6.01	67.76	5.02	40.02
27	4.47	9.38	3.89	4.70	64	4.81	11.93	4.27	6.05
28	4.59	13.73	4.18	6.05	65	3.80	19.42	3.20	8.41
29	4.48	7.94	3.75	4.86	66	4.71	19.25	4.14	10.18
30	4.56	8.84	4.19	8.28	67	7.12	17.33	6.58	9.00
31	5.05	6.77	4.71	5.50	68	4.62	7.03	3.94	4.99
32	6.54	47.70	5.68	21.94	69	4.94	6.80	4.39	5.17
33	5.27	7.80	5.16	7.70	70	7.04	45.64	6.43	25.65
34	7.01	16.82	6.36	16.44	71	4.06	7.30	3.26	3.93
35	5.76	28.87	5.36	15.45	72	4.88	11.02	4.59	4.94
36	5.27	9.90	5.08	5.92	73	4.92	10.85	4.66	5.80
37	4.49	6.61	3.42	4.00	74	4.87	8.82	4.39	6.47

Note: The note shown in the Table 6.21 applies to the analysis results presented in this table.

Table 6.24

The CAVs of Events Found Statistically Significant to be Classified as SAs, but Not Preceded by APAVs During the Post-reform Period.

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
1	4.48	5.82	4.00	2.92	74	4.79	5.11	4.52	4.04
2	4.73	5.15	4.43	3.04	75	5.51	6.70	5.75	1.81
3	4.84	7.21	4.34	1.38	76	4.89	6.49	4.51	3.84
4	4.53	9.08	4.19	4.07	77	4.91	5.60	4.69	3.64
5	4.06	4.65	4.03	2.59	78	4.80	5.46	4.28	3.88
6	4.99	8.89	4.50	0.64	79	6.76	9.62	6.16	5.17
7	4.98	6.37	4.30	3.72	80	4.75	5.16	4.32	2.64
8	4.09	4.61	3.94	2.75	81	4.89	11.86	4.78	4.60
9	4.87	6.40	4.99	0.05	82	4.76	5.06	4.34	1.93
10	5.21	10.02	4.77	2.26	83	6.80	11.17	6.50	1.15
11	4.86	6.91	4.47	3.21	84	4.89	6.82	4.14	2.57
12	4.34	6.41	3.49	2.45	85	4.45	4.49	3.79	1.02
13	5.06	10.15	4.67	4.55	86	5.00	9.08	5.81	5.11
14	5.49	6.21	5.29	2.46	87	5.34	7.24	5.28	2.39
15	4.75	5.91	4.47	2.88	88	5.54	6.76	4.50	3.54
16	4.64	5.12	3.93	1.24	89	4.66	6.25	4.00	2.43
17	5.02	10.81	4.74	4.17	90	5.05	6.20	4.54	2.93
18	4.96	5.42	4.79	1.20	91	5.32	5.56	4.91	0.25
19	4.63	4.81	4.09	1.31	92	4.95	6.66	4.35	3.83
20	4.36	5.09	3.96	1.59	93	5.04	6.76	5.53	3.15
21	5.13	5.41	4.87	2.37	94	5.00	11.54	4.53	2.25
22	4.97	16.06	4.23	0.13	95	4.92	5.77	5.05	3.06
23	4.69	8.25	3.82	2.70	96	4.46	5.62	3.45	3.19
24	4.97	5.33	4.81	3.22	97	5.18	9.35	5.61	3.47
25	5.21	6.78	4.85	3.57	98	5.06	8.98	4.79	0.16
26	4.86	5.18	4.82	2.80	99	4.82	9.54	4.69	1.51
27	5.35	5.93	5.41	4.21	100	4.78	5.49	3.99	3.01
28	4.97	5.70	5.49	2.92	101	4.93	6.69	4.63	1.24
29	4.54	7.99	4.00	2.19	102	5.14	10.32	4.90	2.46
30	4.94	7.28	4.77	3.06	103	5.10	6.97	5.11	1.72

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
31	4.72	8.31	4.31	2.38	104	4.70	8.47	4.35	3.93
32	5.12	6.94	5.23	1.32	105	5.11	10.42	5.02	3.91
33	4.75	5.39	4.27	2.21	106	5.14	9.28	5.32	5.13
34	5.08	6.86	4.32	0.42	107	5.21	5.55	5.52	4.23
35	4.95	6.79	4.75	3.92	108	4.76	9.46	4.34	1.13
36	5.24	8.99	5.02	2.19	109	5.04	7.58	5.12	4.24
37	5.03	10.85	4.75	4.56	110	4.81	6.79	4.45	1.32
38	4.98	5.30	4.07	1.87	111	4.84	6.82	4.16	1.38
39	4.35	4.76	3.64	2.82	112	6.89	9.76	6.84	6.03
40	3.96	6.44	3.22	2.92	113	6.56	11.83	5.57	3.13
41	4.23	6.21	3.54	0.29	114	4.85	6.96	4.42	3.01
42	4.81	6.22	4.71	1.63	115	4.99	5.88	5.03	1.21
43	4.68	5.06	4.03	2.17	116	4.51	7.44	3.70	3.03
44	5.16	7.24	4.36	2.33	117	4.83	6.45	4.54	1.66
45	6.74	21.22	6.25	5.92	118	3.43	6.24	3.68	2.77
46	4.76	5.08	4.24	1.64	119	5.32	9.73	5.35	4.71
47	3.98	9.87	3.23	2.32	120	7.46	10.24	7.63	6.11
48	4.25	6.77	3.47	3.00	121	5.26	5.93	4.98	3.43
49	4.71	5.50	4.02	0.24	122	4.91	7.55	5.04	0.79
50	4.90	5.23	4.24	4.12	123	4.98	5.35	4.67	1.91
51	5.48	8.22	5.72	2.05	124	4.93	5.80	4.74	2.89
52	5.09	5.53	4.96	3.83	125	3.82	4.66	3.75	2.56
53	4.58	5.16	3.85	2.13	126	4.71	5.96	3.90	1.30
54	4.61	7.51	3.92	2.14	127	2.55	2.82	2.15	1.37
55	4.90	5.39	4.46	3.36	128	5.12	7.83	5.02	2.31
56	4.82	5.11	4.87	4.65	129	3.99	5.12	3.44	2.77
57	4.28	6.38	3.39	3.14	130	5.06	10.93	4.56	3.57
58	4.85	5.49	4.37	2.99	131	4.97	7.09	4.68	3.24
59	5.49	7.36	5.69	2.64	132	4.62	5.62	4.28	1.57
60	4.49	5.61	3.58	3.15	133	4.78	5.98	4.00	2.44
61	5.47	9.09	5.57	4.62	134	4.09	6.25	3.32	1.85
62	5.15	5.68	5.93	2.73	135	4.89	6.47	4.61	2.91
63	4.94	7.15	4.60	0.52	136	4.82	5.71	4.58	1.29
64	6.38	7.98	5.18	1.84	137	4.00	5.37	3.24	2.94

No. of Events	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**	No. of Events continued	Simulated post-event CAVs 99% quantile threshold	Actual post-event CAVs (-2,+2) Sig. at 1%*	Simulated pre-event CAVs 90% quantile threshold	Actual pre-event CAVs (-2,-1) Sig. at 10%**
65	4.78	5.41	4.37	2.86	138	4.63	7.70	4.25	3.89
66	5.04	6.14	5.04	3.01	139	4.99	5.11	4.57	3.44
67	5.25	6.05	4.69	1.97	140	4.75	8.71	4.71	4.05
68	4.73	6.11	4.06	3.81	141	5.21	5.70	5.18	1.78
69	5.02	5.87	4.08	3.12	142	4.87	5.72	4.77	3.18
70	4.75	7.20	4.12	3.15	143	4.88	8.05	4.92	4.59
71	4.73	5.88	4.13	2.42	144	4.67	7.53	4.04	2.99
72	5.24	5.96	5.24	2.29	145	4.45	5.01	3.66	1.77
73	4.09	4.96	4.35	2.01					

Note: The note shown in the Table 6.22 applies to the analysis results presented in this table.

Figure 6.9 and Figure 6.10 provide a comparative analysis of the total count of valid announcements examined during the relevant period and the proportion that meet the 1% significance level for classification as SAs. The process of comparison enables assessment of whether an increase in the number of SAs can be attributed to a corresponding increase in the sample size of events analysed during each respective period. The timeframe for each year concludes on 25 April. Also, the first half of 2016 falls within the pre-reform period whereas the latter half corresponds to the post-reform time.

When looking at the lower and greater ratio of SAs in respective to the sample size of year-on-year events, Figure 6.9 shows that the proportion of SAs in 2014 is the lowest for all years, at 9.60% out of a total of 177 events. The highest percentage of SAs relates to the year 2012 and is 26.90% out of a sample of 145 events. Although the sample size in 2014 is larger than that in 2012, the percentage of estimated SAs for 2014 is smaller than for 2012.

As for the sample of the post-reform period, Figure 6.10 shows that the year 2019 has the lowest percentage of SAs (17.66%), but the largest number of events, totalling 351 announcements. In contrast, the year 2020 has 228 events few events but the percentage of SAs in that year is 2.67% larger than is seen in 2019. When comparing the overall percentage of SAs alongside the full samples for the two periods, the figures show that despite the total number of events examined for the post-reform period being higher than that analysed for the pre-reform period, the percentage of SAs in the earlier period is greater than that of the later period. In line with the conclusion of the returns event study analysis, it can be inferred that the based on the VMCMs the percentage of SAs is not associated with an increase in sample size of events on an annual basis.

Figure 6.9

The Percentage of Significant Announcements Among Total Announcements Over the Pre-reform Period According to the Volume Analysis.

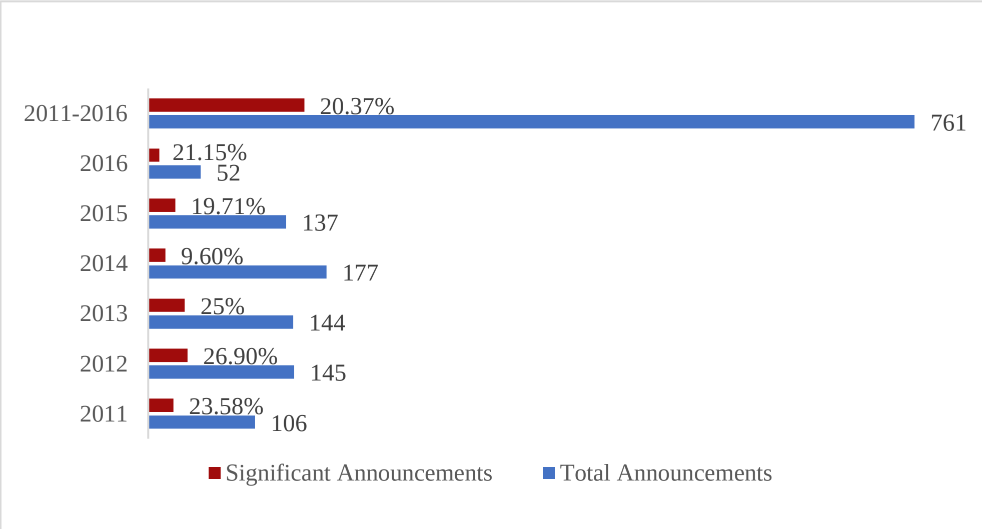


Figure 6.10

The Percentage of Significant Announcements Among Total Announcements Over the Post-reform Period According to the Volume Analysis.

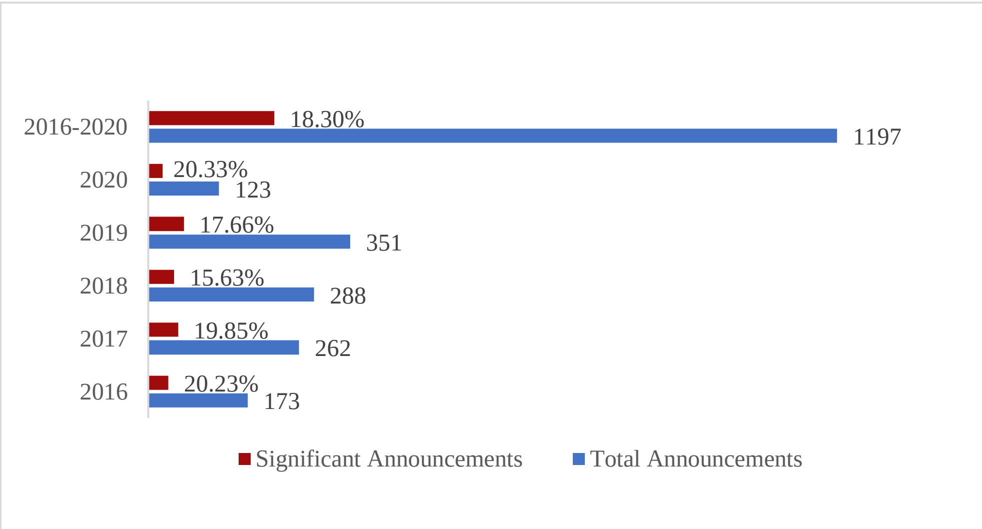


Table 6.25 summarises the results for the VMCMs analysis of the Tadawul over the relevant period, showing the total number of original events analysed, the number of events identified as SAs and number of events for which APAVs were observed.

Table 6.25

The Market Cleanliness Measure of Trading Volume Throughout the Relevant Period.

Panel A: The VMCMs during pre-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APAVs***	MCM****
2011	106	25	14	56.00%
2012	145	39	15	38.46%
2013	144	36	17	47.22%
2014	177	17	5	29.41%
2015	137	27	6	22.22%
2016 (1st half)	52	11	6	54.55%
2011-2016	761	155	63	40.65%
Panel B: The VMCMs during post-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APAVs***	MCM****
2016 (2nd half)	173	35	13	37.14%
2017	262	52	16	30.76%
2018	288	45	13	28.88%
2019	351	62	25	40.32%
2020	123	25	7	28.00%
2016-2020	1197	219	74	33.79%

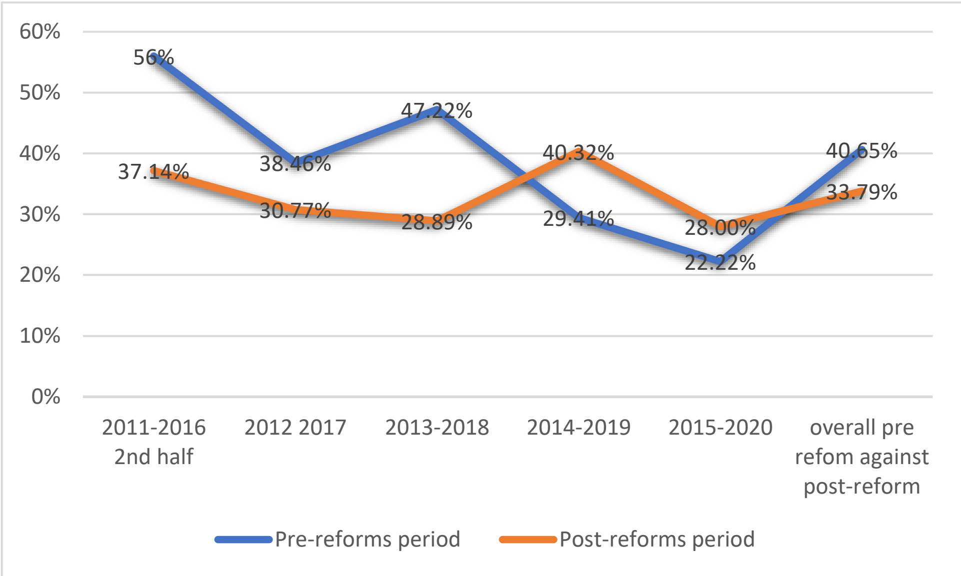
Note: *Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APAVs were observed at a statistical significance level of 10%. ****The ratio of SAs that were preceded by APAVs.

As indicated in Panel A of Table 6.25, the VMCMs suggest that among 761 announcements for the pre-reform period are 63 instances of APAVs observed prior to a total of 155 SAs. The ratio of APAVs to SAs during the pre-reform period is estimated at 40.65%. Panel B reports VMCMs for the post-reform period, showing that of 1,197 events 219 are SAs, 74 of which were preceded by APAVs. The data in Panel B indicate that the overall VMCMs is 33.79% for the post-reform period, 6.86% lower than for the preceding period.

The analysis, as shown in Figure 6.11, confirms that the overall VMCMs for the post-reform period is lower than that for the pre-reform period. However, when a comparison is made on an annual basis, the VMCMs show an increase in the ratio of APAVs by 10.91% for the year 2019 compared with 2014. Similarly, the year 2020 presents a higher value of the proportion of APAVs, by 5.78%, compared with 2015. However, the overall VMCMs is lower after the introduction of financial reforms.

Figure 6.11

Yearly VMCMs During Pre- and Post-reform Periods.



To answer MRQ_2 and establish the statistical significance of the observed difference, a *z*-test, described by Equation (6.1), is used to assess the difference in the ratio of APAVs between the two periods (i.e., before and after 25 April 2016). The test assumes that each event in a specific group has an equal probability of being an APAV, irrespective of any other explanatory variables. In other words, the likelihood of an event occurring is not contingent on other occurrences. Table 6.26 shows the difference in the VMCM for the post-financial reforms period compared to the pre-financial reforms period.

Table 6.26

Test Statistics for the Difference in VMCMs between the Pre- and Post-reform Periods.

Period	SAs	APAVs	Measure	Difference
pre-financial reforms	155	63	40.65%	6.86% (p-value=0.087)
post-financial reforms	219	74	33.79%	

The VMCMs shows a decrease of 6.86% following the introduction of financial reforms, thus the null hypothesis is rejected (z = 1.356, p- = 0.087) as the reduction in the VMCMs after the introduction of financial reforms is statistically significant at 10%.

The following outcomes relate to RSQ_2. As explained in Section 5.7, the application of the ADL-GARCH method foe volume analysis relies on four scenarios that delineate the process of selecting an appropriate model to address the problem of serial correlation and heteroscedasticity in volume data. The analysis is conducted on a total of 1,958 announcements over the relevant period, with 761 of those corresponding to the pre-reform period and 1,197 to the post-reform period. Before employing the correction procedures, described in Table 5.5 in Section 5.7.2, the Engle's test reveals that 69.65% of events in the first period and 69.51% of those in the second period experience heteroscedasticity. Following the refinement made to mitigate the effects of heteroscedasticity using the GARCH (1,1) and conducting a second Engle's LM test, the corresponding figures for the pre- and post-reform period decline to 2.37% and 4.26%, respectively. Regarding the serial correlation, the early findings yielded from the Durbin–Watson test reveal signs of serial correlation in 92.51% of announcements in the pre-reform sample, and 87.80% of announcements in post-reform sample. When the correction for serial correlation is made by employing the ADL model described by Equation 5.30, and subsequently conducting a second Durbin-Watson test, those figures drop to 0.39% and 0.33% for the pre-reform and post-reform sample, respectively. After implementation of the corrective measures outlined, the analysis finds that 97.24% of the events (i.e., 740 out of 21 events) evaluated for the pre-reform period and 95.41% of the events (i.e., 1,142 out of 55 events) assessed over the post-reform period satisfy the assumption of homoscedasticity and no serial correlation. The outcomes are reported in Figure 6.12 and Figure 6.13 for the events analysed over the pre- and post-reform period, respectively.

Figure 6.12

Correction for Serial Correlation and Heteroscedasticity According to Model Selection for Volume Analysis During the Pre-reform Period.

Scenario	**No change**		**Corrected serial correlation**	**Corrected heteroscedasticity**	**Corrected serial correlation & heteroscedasticity**	**Total events**
No SC & no HK	8					8
Serial correlation only			220			220
Heteroscedasticity only	0			31		31
Serial correlation & Heteroscedasticity	3*	18**			481	26
Total event	29		220	31	481	761

* Stands for the number of events that still exhibit serial correlation.
* * Stands for the number of events that still exhibit heteroscedasticity.

Figure 6.13

Correction for Serial Correlation and Heteroscedasticity According to Model Selection for Volume Analysis During the Post-reform Period.

Scenario	**No change**		**Corrected serial correlation**	**Corrected heteroscedasticity**	**Corrected serial correlation & heteroscedasticity**	**Total events**
No SC & no HK	25					25
Serial correlation only			336			336
Heteroscedasticity only	46			70		116
Serial correlation & Heteroscedasticity	4*	5**			711	720
Total event	80		336	70	711	1197

* Stands for the number of events that still exhibit Serial correlation
* * Stands for the number of events that still exhibit Heteroscedasticity

6.4.1 The Results of the Relationship Between the Return and Volume Analyses

The discussion in this section addresses RQ_7 by assessing the relationship between the analyses of return and trading volume. An analysis is performed to examine if there is a relationship between the MCMs estimated in the return and volume analyses; that is, are SAs accompanied by APPMs also accompanied by APAVs? H_{09} posits that there is no significant relationship between the MCMs for the return and volume analyses where SAs preceded by APPMs were not simultaneously preceded by APAVs.

After analysing the results from the return and volume event studies and identifying SAs for which APPMs are detected, along with those that experienced APAVs, an investigation was conducted as follows. The analysis is carried out to see how many events identified as SAs fall into the following four categories as follows. First, SAs preceded by both APPMs and APAVs. Second, SAs preceded only by APPMs with no occurrence of APAVs. Third, SAs preceded by APAVs but no signs of APPMs. Forth, neither both instances of APPMs nor AAPAVs have been observed ahead of SAs. Table 6.27 and 6.28 present results from the analysis of the relationship between the return and volumes analysis for the pre- and post-reform periods, respectively.

Table 6.27

Relationship Between the Return and Volume MCMs for the Pre-reform Period.

	APAVs	**Not APAVS**
APPMs	**7**	**31**
Not APPMs	**56**	**667**

Table 6.28

Relationship Between the Return and Volume MCMs for the Post-reform Period.

	APAVs	**Not APAVS**
APPMs	**7**	**37**
Not APPMs	**67**	**1086**

The sums of observations in both tables are the overall sizes of the samples during the relevant period. Table 6.27 pertains to the sample over the pre-reforms period (i.e., 761 announcements) while Table 6.28 relates to the sample for the post-reforms period (i.e., 1197 announcements). To explain the tables, the cells highlighted in grey represent the announcements in which there is a match by the return and the volume analyses. To be more specific, the number 7 in both tables stands for the first category where both APPMs and APAVs were concurrently detected ahead of SAs. The large numbers (i.e., 667 and 1086) denote to the fourth group in which the events are classified as not leading to APPMs (i.e., no abnormal pre-announcement price movements in the return analysis) and as not experiencing APAVs (i.e., no abnormal pre-announcements volumes in the volume analysis).[46]

As for the sample over the pre-financial reforms in Table 6.27, the first row displays that of the 38 which are determined to be APPMs, 7 announcements were jointly classified as having both occurrences of the APPMs and the APAVs. The same row in Table 6.27 shows that 31 announcements are identified to be APPMs but not APAVs. The first column of Table 6.28 reports that of the 74 announcements were identified as APAVs and 7 of them were simultaneously accompanied by APPMs. Further interpretations of these findings are addressed in the discussions of Section 7.2.4.

6.5 Chapter Summary

This chapter presented the comprehensive findings of the Tadawul's MCMs in the return and volume event study, covering the periods both preceding and following the introduction of financial reforms. The MCMs for both the return and volume analysis provide evidence of the occurrences of APPMs and APAVs ahead of SAs over the relevant period. All the analyses are mutually supporting, indicating a reduction in MCMs following the implementation of financial reforms (specifically, from 26 April 2016 to 25 April 2020) compared to the time before the changes (from 26 April 2011 to 25 April 2016).

[46] The sum of the APAVs in Table 6.27 and 6.28 are same total of events that categorised as APAVs, reported in Tables 6.21 and 6.23. However, the total number of APPMs in the tables refers to overall number of APPMs derived from the analysis of both the MM and ADL-GARCH approaches.

Nevertheless, the findings of the return event research conducted using the MM and ADL-GRCH methods suggest that the observed decline in the metrics did not exhibit statistical significance. The supplementary robustness checks indicate that there was no statistically significant difference between the first and second half of the relevant time, even after employing multiple event windows of different durations and controlling for sample-specific characteristics. Conversely, the volume event study indicates that there was a statistically significant decrease in the measures after the implementation of the financial reforms. The chapter shows the findings on the relationship between the MCMs of the return and volume analysis indicating the presence of significant correlation.

Chapter 7: Discussion and Conclusion

7.1 Introduction

This chapter presents the findings and discussion of key points addressed in this research, including the thesis statement, the research objectives alongside their respective questions and the hypotheses examined in Chapter 5. The study limitations as well as the implications arising from the study and directions for future work are discussed in this chapter.

The remainder of the chapter is structured as follows. Section 7.2 addresses the six objectives of the study by outlining their relevant hypotheses and the findings relating to the relevant questions. Section 7.3 highlights the implications of the study. This is followed by a discussion of the limitations along with suggestions and opportunities for future research in Section 7.4. Section 7.5 concludes the chapter by summarising and bringing together the key findings.

7.2 Study Objectives and Key Findings

This section attempts to restates the principal aims and objectives of this research, and tests the research hypotheses formulated in Chapter 4, drawing from the findings presented in Chapter 6, which are then discussed in line with the relevant literature. Although Chapter 6 offers a comprehensive elucidation of the study findings, it is beneficial to revisit the research questions to appreciate how the objectives have been accomplished, by linking them with their relevant hypotheses and questions, as demonstrated in the following sections.

7.2.1 Findings and Discussion Relating to the First Objective: Returns Analysis

The first objective sought to estimate the level of potential insider trading in the Tadawul before (26 April 2011 to 25 April 2016) and after (26 April 2016 to 25 April 2020) the introduction of financial reforms based on a returns event study employing the MCMs. To this end, the study posed the following research questions (RQs):

RQ$_1$. Is there evidence of SAs wherein firms announcements have a significant impact on the distribution of CARs during the post-event window?

RQ$_2$. Is there evidence of APPMs wherein firms announcements have a significant impact on the distribution of CARs during the pre-event window?

To address RQ$_1$ and RQ$_2$, the present study formulated two null hypotheses (H_{04} and H_{05}),[47] which relate to the investigation of SAs and examination of whether there is evidence of APPMs, respectively, as follows:

H_{04}: The announcement had no significant impact on the distribution of CARs over the post-event window.

H_{05}: The announcement had no significant impact on the distribution of CARs over the pre-event window.

Null hypotheses H_{04} and H_{05} were tested using two approaches. The first was the conventional market cleanliness measures labelled the MM approach as outlined in Section 5.4. The second approach employed the advanced market cleanliness measures according to the ADL-GARCH approach (ADL-GARCH) described in Section 5.5, to overcome shortcomings with the MM approach. The conclusions drawn from the MM and ADL-GARCH approaches are summarised in Section 7.2.1.1 and 7.2.1.2, respectively.

7.2.1.1 Findings and Discussion Based on the MM Approach

For hypotheses testing based on the MM approach, the analysis was carried out by utilising an OLS market model to estimate the stock ARs, followed by computing the CARs over the event window being tested. Then, the bootstrapping technique, described in Section 5.4.3, was employed to make inferences regarding whether the CARs over the post-event window and the CARs over the pre-event window were statistically significant.

[47] The $H_{01}$and H_{02} pertain to the overarching aims of the study. H_{03} had to be developed following the literature review Chapter4 prior to $H_0$4 and $H_0$5.

Regarding H_{04}, Table 6.2 to Table 6.5, displayed in Chapter 6, report the number of events for the sample covering the relevant period for which the null H_{04} was rejected. The results provide evidence of 55 events identified as SAs over the pre-reform period (24 events in Table 6.2 and 31 events in Table 6.3), and 73 SAs for the post-reform period (see Table 6.4 and 6.5). Regarding H_{05}, Table 6.3 and 6.5 provide evidence showing that there were 31 events (as per Table 6.3) over the pre-financial reforms period and 33 events in Table 6.5 during post-financial reforms period satisfied the determined statistical threshold for being APPMs.

In addressing RQ_1 and RQ_2, the first objective in this section was met by estimating the potential insider trading level in the Tadawul, as measured by a returns event study of the MCMs according to the MM approach, in the periods before and after the introduction of financial reforms. Table 7.1 presents yearly estimates of the Tadawul's MCMs using the MM approach with event window length (–2, +2). The table shows the total number of original events analysed, number of events identified as SAs, and number of events for which APPMs were observed. Panel A shows that 56.36% of SAs were preceded by APPMs during the pre-reform period, compared with 45.20% over the post-reform period as shown in Panel B.

A discussion of findings presented to this point in relation to previous studies is provided in the following section after the findings from the ADL-GARCH approach are presented. This is because the analysis of both methods (i.e., MM and ADL-GARCH) revolves around the identification of instances of APPMs detected ahead of SAs.

Table 7.1

The MCMs Throughout the Relevant Period According to the MM Approach With Event Window Length (–2,+2).

Panel A: The measurements during pre-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2011	106	15	9	60%
2012	145	9	8	88.8%
2013	144	7	3	42.8%
2014	177	16	8	50%
2015	137	4	1	25%
2016 (1st half)	52	4	2	50%
2011-2016	761	55	31	56.36%
Panel B: The measurements during post-financial reforms period				
2016 (2nd half)	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2016	173	12	8	66.6%
2017	262	17	7	38.8%
2018	288	16	5	31.2%
2019	351	11	3	27.2%
2020	123	16	10	62.5%
2016-2020	1197	73	33	45.20%

*Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APPMs were observed at a statistical significance level of 10%. ****The ratio of SAs that were preceded by APPMs.

7.2.1.2 Findings and Discussion Based on the ADL-GARCH Approach

As outlined in Section 7.2.1, the first objective was re-visited using the ADL-GARCH approach. To address RQ_1 and RQ_2 via the ADL-GARCH approach, H_{04} and H_{05} were re-tested through two sub-hypotheses (H_{05a} and H_{05b}). First, security abnormal returns were estimated using the OLS market model. Second, H_{05a}, which states that the daily variance in estimation errors of the OLS market model is constant over time, was tested using Engle's LM test to verify the presence of heteroscedasticity. Third, the null H_{05b}, which assumes that the error term of the OLS market model is not serially correlated, was examined using the Durbin–Watson test to verify the presence of serial correlation. The analysis employed the model selection approach described in Section 5.5 using a sample consisting of 1,958 announcements, 761 of which corresponded to the pre-reform period and 1,197 to the post-reform period.

When testing the H_{05a}, the preliminary Engle's test suggested that heteroscedasticity was present in 37.06% of the pre-reform sample and 79.63% of the post-reform sample. In terms of serial correlation, the early findings yielded from the Durbin-Watson test revealed that signs of serial correlation were seen in 92.51% and 87.80% of the pre- and post-reform announcements sample, respectively. However, when the correction for heteroscedasticity was applied, these figures declined to 7.75% and 13.27% for the pre- and post-reform period, respectively. After correcting for serial correlation alone without considering the joint presence of both features, the results showed no evidence of the presence of serial correlation in either period. Although a few events still exhibited signs of both features, as shown in Figure 6.7 and 6.8, the analysis concluded that 697 events (i.e., 91.59%) evaluated during the pre-reform period and 1,094 events (i.e., 91.40%) assessed during the post-reform period met the assumptions of homoscedasticity and no serial correlation of the errors for OLS estimators.

These findings hold significant relevance for studies focused on examining stock returns through daily observations in the context of the Tadawul. The results from this study are supported by those of previous studies of the Tadawul such as Mhmoud and Dawalbait (2016) and Sulaiman (2011), who report that the conditional volatility of stock returns exhibits a significant degree of persistence. Further, Wasiuzzaman (2018) finds that the Tadawul is influenced by seasonality and experiences a significant increase in volatility during the Hajj pilgrimage season and Ramadan month. Shaik (2021) finds that the post-event period witnesses a surge in stock volatility in the Tadawul, as opposed to the pre-event period, resulting in a negative average return. Moreover, Abdumolah (2010) examines efficiency of some stock markets in the MENA region including the Tadawul, considering the effects of thin trading. Abdumolah's (2010) findings are broadly similar to those of Harrison (2012), showing that the GARCH model offers notable benefits by reducing the bias. Along similar lines, the current study confirms the strong need to design procedures that handle the impact of serial correlation and heteroscedasticity as well as their respective implications when conducting an event study relying on daily data observations. The models used here exhibit superior fit to empirical time series data and were largely able to overcome undesirable data features.

After testing the partial hypotheses of H_{04} and H_{05} (i.e., H_{05a} and H_{05b}), bootstrapping technique was performed to test the H_{04} and H_{05} by assessing the statistical significance of CARs over the post-event window for H_{04} and those during the pre-event window for H_{05}. In addressing RQ_1, the hypothesis testing related to H_{04} according to the ADL-GARCH method, did not permit rejection to H_{04} for a number of 76 events because they were determined as SAs over the pre-financial reforms period, 54 events reported in Table 6.9 and 22 events in Table 6.10. The hypothesis testings for the sample of the post-reforms period failed to reject the null H_{04} for 123 events as they met the predetermined threshold for being SAs (93 events as per Table 6.11 and 30 events as reported in Table 6.12).

With regard to the investigation pertaining to RQ_2, the results derived using the ADL-GARCH approach yielded evidence to reject the null H_{05}, which is associated with examination of the presence of statistically significant APPMs over the pre-event window. It was observed that there were 22 APPMs instances during the pre-reforms as per Table 6.10, whereas the post-reforms period witnessed 30 incidents of APPMs as reported in Table 6.12

Having addressed RQ_1 and RQ_2 using the ADL-GARCH approach, the relevant objective was accomplished by estimating the MCMs for the Tadawul over the first and the second halves of the relevant period. Table 7.2 presents annual outcomes for the Tadawul's MCMs based on the ADL-GARCH method using an event window duration of (–2,+2).

Table 7.2 shows the total number of announcements, SAs and APPMs. The values in Panel A are MCMs for the pre-reform period, revealing that 28.94% of the SAs experienced APPMs. Panel B indicates that APPMs took place prior to 24.39% of SAs over the post-reform period.

Table 7.2

The MCMs Throughout the Relevant Period According to the ADL-GARCH Approach with Event Window Length (–2,+2).

Panel A: The measurements during pre-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2011	106	18	7	38.8%
2012	145	11	4	36.3%
2013	144	7	1	14.2%
2014	177	21	4	19%
2015	137	12	5	41.6%
2016	52	7	1	14.2%
2011-2016	761	76	22	28.94%
Panel B: The measurements during post-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APPMs***	MCM****
2016	173	19	7	36.8%
2017	262	29	6	20.6%
2018	288	33	7	21.2%
2019	351	22	3	13.6%
2020	123	20	7	35%
2016-2020	1197	123	30	24.39%

*Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APPMs were observed at a statistical significance level of 10%. ****The ratio of SAs that were preceded by APPMs.

Few empirical studies investigate insider trading practices in the Tadawul; however, the findings of the present study can be compared with relevant event studies that examine the existence of significant CARs. The evidence provided by this study of the statistical significance of CARs surrounding firms announcements is in line with the findings of Syed and Bajwa (2018), whose event study analysis documents the presence of significant CARs—particularly from day -9 to day -4 in the pre-event window—of earnings announcement dates of firms listed in the Tadawul. Furthermore, Felimban et al. (2018) provide evidence of significant CARs before dividend reduction announcements as well as immediately following board meetings, which supports the conclusion that GCC region markets, including the

Tadawul, exhibit inefficiency because of the leakage of information as well as possible insider trading ahead of negative news announcements and the sluggish adjustment of share prices after the release of positive news. In their analysis of all stocks listed on the Tadawul, Bash and Alsaifi (2019) calculate the CARs around uncertain bad events and find evidence for a very strong negative impact on the returns of the Tadawul, suggesting that the observed negative response is primarily influenced by domestic investors.

Regarding the evidence for SAs, which pertain to the examination of CARs over the post-event window, the results support those of Alshammari and Ory's (2023) event study on a unique dataset of religious downgrade and upgrade announcements made by imams.[48] Their findings suggest the presence of significant negative CARs over the post-event window spanning +1 to +3 before 74 negative events of downgrade announcements and positive CARs over a post-event window starting from 0 to +1 of 83 upgrade announcements. Sayed and Eledum (2021) find that confirmation of the first COVID-19 case announced by the authorities in Saudi Arabia had a significant negative effect on the Saudi stock market in the first nine days of the event window. Despite difference in the types of announcements, these studies employ a similar method to the current study, demonstrating the efficacy of this methodology. Further, the findings of the present study are consistent with earlier research.

From a methodological point of view, evidence presented by Monteiro et al. (2007) suggests that the ADL-GARCH method shows superior capability for accurately modelling stock behaviour, and returns lower MCMs than does the MM approach, similar to the findings of the current study. First, all MCMs obtained using the ADL-GARCH method across the two periods were smaller than those from the MM method. Second, the ADL-GARCH method used in the present study proved highly effective in precisely modelling

[48] Imams refer to a number religious scholar who classify the firms listed on the Tadawul in accordance with Sharia Laws to pure-Islamic, mixed-Islamic, and non-Islamic by conducting assessment approximately once a year. The classification of upgrade announcement denotes to a case in which a given firm that was considered non-Islamic adhered the Sharia rules then reclassified as Islamic and vice versa downgrade announcements.

ARs in a significant portion of valid announcements. Interestingly, a substantial portion of the time series estimated using the MM approach—specifically 56.6%—showed signs of either heteroscedasticity, serial correlation or both. However, the figures of these issues were significantly lower with the ADL-GARCH approach, as shown in Figure 6.7 and 6.8. The empirical findings document a significant presence of heteroscedasticity and serial correlation in the residuals of the returns series. Importantly, the findings from ADL-GARCH approach expose a weakness in the MM approach and serve as a cautionary message to future event studies on the Tadawul that rely solely on the market model, disregarding the impacts of heteroscedasticity and serial correlation. The conclusions drawn from the ADL-GARCH method are more accurate and reliable.

Although the market cleanliness methodologies are utilised in studies across different countries, an international comparison of the Tadawul's MCMs with those of different countries may lack credibility of direct comparison. This decision was prompted by the study of Goldman et al. (2014), who highlight that differences among markets in corporate governance and legislative frameworks may reduce the comparability of the MCMs in direct comparisons across countries. Without going into detail, the market cleanliness studies conducted by Goldman (2014), Dubow and Monteiro (2006) and Monteiro et al. (2007) for the UK market and the ASIC (2016, 2019) for the Australian equity market had lower MCMs than those of the Tadawul.

All in all, the first objective of the study was met by estimating the level of potential insider trading in the Tadawul before and after the introduction of the financial reforms based on a returns event study of MCMs that used two methods (i.e., MM and ADL-GARCH). The main conclusion from quantitative analysis using these two approaches, which agreed with each other, indicate that the level of potential insider trading as measured by MCMs declined after the introduction of financial reforms. However, the question is whether the observed decline over the subsequent period is statistically significant than that for the preceding period. The answer to this question relates to the principal aim of this research as we shall see in Section (7.2.5).

7.2.2 Findings and Discussion Relating to the Second Objective

The second objective was to evaluate whether the use of several event windows with different lengths has a significant effect on the MCMs between the pre- and post-reform periods. Therefore, the study asked the following:

RQ_3. Does the use of multiple event windows with varying lengths have a statistically significant impact on the results for the MCMs between the two periods?

The study considered the potential influence of the event window length on the calculation of CARs to ensure the robustness of the findings. Thus, based on an extensive review of the relevant literature discussed in Section 4.3.2, this study tested the following hypothesis:

H_{03}: The difference in the MCMs between the two periods is insignificant regardless of the length of the event window.

In testing H_{03}, a preliminary analysis was conducted by calculating the CARs over several event windows with varying lengths: (–2, +2), (–5, +5) and (–10, +10). The findings presented in Panel A of Table 6.7 in Chapter 6, which are based on the analysis performed using the MM approach, show that there were differences in the MCMs between the two periods (i.e., pre- and post-reform periods) for several window lengths. The *z*-test described in Equation (6.1) was performed to test H_{03}. The test did not permit the rejection of the null, because the difference between event window lengths over both periods was insignificant. This conclusion was based on the findings obtained using the MM approach.

The results according to the ADL-GARCH approach presented in Panel B of Table 6.14 are consistent with the conclusions from the MM approach. The test results did not provide sufficient evidence to reject the null hypothesis (i.e., H_{03}) because the observed difference in the MCMs between the two periods was statistically insignificant regardless of the length of the event window.

This analysis leads to the conclusion that an event window length of (–2, + 2), which consists of two days immediately prior to the event day and two days after, provides the cleanest evidence of potential insider trading activities because it captures a larger number of APPMs than other window durations. Although there may be no perfect window length, the length of (–2, +2) was associated with the highest significance level and the smallest *p*-value in favour of the alternative hypothesis among all lengths examined. The findings presented in this study are similar to those reported by Monteiro et al. (2007) and Goldman (2014), that the two-day window leading up to an announcement has the greatest likelihood of detecting instances of information leakage and insider trading activities. In addition, those authors conclude that the observed reduction in the MCMs their analysis is not influenced by a particular event window length.

7.2.3 Findings and Discussion Relating to the Third Objective

The third objective was to analyse whether the changes in the MCMs in the returns analysis may be explained by other factors. This led to the following RQ being posed:

> **RQ_4.** To what extent do sample-specific characteristics of the seven factors examined have an impact on the MCMs?

After estimating the MCMs, the study strived to ensure that the MCMs was not influenced by other factors. Based on the review of the relevant literature presented in Chapter 4, the study formulated the subsequent hypothesis:

> H_{06}: The MCMs is not significantly influenced by the sample-specific characteristics firm size, liquidity, volatility, information asymmetry, trading activity and absolute CARs.

To address H_{06}, the study considered a robustness check of the findings regarding the MCMs by conducting an additional econometric analysis using the logistic regression model. The results of the logistic regression analysis shown by Table 6.18 in Chapter 6 demonstrate that none of the included factors other than trading activity had a statistically significant effect on the likelihood of the occurrence of APPMs.

One possible explanation for the significance of trading activity may be due to attentive trading to identify price-sensitive information and establish positions in advance of an official release (Alldredge, 2015). Further, it can be interpreted from the significant increase in equity volume in stocks accessible by informed traders about upcoming earnings news as noted by Akey Gregoire and Martineau (2022), who studied the ability of market makers to identify and react to sudden surges in informed trading. Moreover, because of the different sources of information available to investors and different levels of accuracy of private prior information, responses to new information also differ, resulting in changes in trading volume activity (Flemban, 2018).

In a further interpretation, Bolandnazar et al. (2020) examine trade patterns after the US' Securities and Exchange Commission (SEC) unintentionally disseminated securities disclosures to a limited number of investors a few seconds prior to the official release to the broader market and demonstrate that informed investors traded more aggressively as the expected time of publication of news approached. Similarly, Biggerstaff et al. (2020) note that insider traders increase their trading over a shorter horizon duration when informational advantage is short lived. Such trading activities may have the potential to increase levels of trading activity during the period preceding an official announcement. In the Tadawul context, Alhussayen (2022) note that investors who possess private information about which they are overly confident tend to prioritise it over public information, which results in a steady rise in the trading volume in the short term. Overall, it is possible to note that the instances of APPMs in the current study coincided with a rise in trading volume activity surrounding days on which announcements were made.

With respect to other factors that had no significant effect on the MCMs, the results of the present study are broadly similar to those of Monteiro et al. (2007), who developed the market cleanliness methodology. They find no evidence that changes in the factors they examine have a significant effect on the measure of market cleanliness for their analysis of a takeover sample.[49] However, they report that there is little evidence that firm size has a significant effect on the odds in favour of an APPM. In light of the results from several logistic regression analyses explained in Chapter 6, the conclusions are reassuring. The statistics showed a limited effect of one factor, as explained above, while the remaining factors did not exhibit significant effects on the measure of market cleanliness.

7.2.4 Findings and Discussion Relating to the Fourth Objective: Volume Analysis

The fourth objective of the study was to estimate the level of potential insider trading in the Tadawul before and after the introduction of financial reforms, using a volume event study of MCMs. The following RQs were thus posed:

RQ_5. Is there evidence of SAs wherein firms announcements have a significant impact on the distribution of CAVs over the post-event window?

RQ_6. Is there evidence of APAVs wherein firms announcements have a significant impact on the distribution of CAVs over the pre-event window?

To address RQ_5 and RQ_6, the study tested two null hypotheses:

H_{07}: The announcement had no significant impact on the distribution of CAVs over the post-event window.

H_{08}: The announcement had no significant impact on the distribution of CAVs over the pre-event window.

[49] Section 4.6 discusses the factors examined by Monteiro et al., (2007).

H_{07} and H_{08} were tested via sub-hypotheses H_{07a} and H_{07b}, which required examination for the presence of heteroscedasticity and serial correlation. First the stock AVs were estimated using a trading volume market model. Then, H_{07a} was tested using Engle's LM test to verify the presence of heteroscedasticity and H_{07b} was tested by employing the Durbin–Watson test to investigate the existence of serial correlation. The analysis was performed using the model selection outlined in Section 5.6, for a sample of 1,958 announcements. Of these, 761 were from the pre-reform period and 1,197 from the post-reform period.

The preliminary results obtained using Engle's LM test showed that 69.65% of data for the first period and 69.51% for the second period were not homoscedastic. The Durbin–Watson test indicated that 92.51% of the pre-reform data and 87.80% of the post-reform data were serially correlated. Following correction for heteroscedasticity, the corresponding figures for the pre- and post-financial reform periods declined to 2.37% and 4.26%, respectively. When a rectification for serial correlation was made, those figures dropped to 0.39% and 0.33% for the samples pre- and post-reform, respectively. Upon implementation of the outlined corrective measures, the analysis indicated that 97.24% of the events (i.e., 740 out of 21 events) evaluated during the pre-reform period and 95.41% of the events (i.e., 1,142 out of 55 events) assessed over the post-reform period satisfied the assumption of homoscedasticity and no serial correlation. The data presented in Figure 6.12 and Figure 6.13 for the pre- and post-reform sample, respectively.

These results echo the earlier findings of Seyyed et al. (2005) who document that Ramadan causes high volatility in trading activities in the Tadawul causing, and the results of Alsubaie and Najand (2009) who examine the volatility–volume relationship in the Tadawul and find a strong consistency of volatility. They suggest that the speed at which new information is received can be a key source of conditional heteroscedasticity at the firm level.

The procedure employed in the current study provided superior results by overcoming issues of undesirable data effects, particularly serial correlation and heteroscedasticity.

Having addressed sub-hypotheses H_{07a} and H_{07b}, the discussion now turns to H_{07} and H_{08}. To test these hypotheses, the CAVs for each firm were calculated and the bootstrap method employed to assess the statistical significance of CAVs over the post-event window for H_{07} and the pre-event window for H_{08}.

In regard to RQ_5 and RQ_6, Tables 6.21 to 6.24, provided in Chapter 6, present the hypothesis testing results, which provide empirical evidence for the presence of significant CAVs surrounding 374 of 1,958 unscheduled announcements issued by companies listed on the Tadawul between 2011 and 2020. With regard to H_{07}, Table 6.21 to Table 6.24 report the number of events in which the H_{07} was not confirmed, among 155 and 219 events over the pre- and post-reform periods, respectively. These events were classified as SAs because they had a significant impact on the distribution of CAVs over the post-event window. Table 6.21 and Table 6.22 show that there were 63 and 92 SAs over pre-reform period. Table 6.23 report 74 SAs and Table 6.24 report 145 SAs during post-reform period. The results of testing null hypothesis H_{08}, which could not be rejected because APAVs were detected in 63 events during the pre-reform period as reported in Table 6.21 and 74 events during the post-reform period as shown in Table 6.23 (see column titled actual pre-event CAVs).

The fourth objective was addressed by estimating the VMCMs of the Tadawul across the periods preceding and following the introduction of financial reforms. Table 7.3 summarises the results for the VMCMs of the Tadawul over the relevant period with the total number of original events analysed, number of events identified as SAs and number of events for which APAVs were observed over the relevant period. As indicated in Panel A of Table 7.3, the VMCMs is 40.65% over the pre-reform period as the APAVs were detected in 31 of

55 SAs. Panel B reports that the VMCMs decrease to 33.79% during the post-reform period, revealing that 73 of 1,197 events were SAs and 33 of them exhibited APAVs.

Table 7.3

The VMCMs Throughout the Relevant Period.

Panel A: The measurements during pre-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APAVs***	MCM****
2011	106	25	14	56.00%
2012	145	39	15	38.46%
2013	144	36	17	47.22%
2014	177	17	5	29.41%
2015	137	27	6	22.22%
2016 (1st half)	52	11	6	54.55%
2011-2016	761	155	63	40.65%
Panel B: The measurements during post-financial reforms period				
Year	No. of Ann*	No. of SA**	No. of APAVs***	MCM****
2016 (2nd half)	173	35	13	37.14%
2017	262	52	16	30.76%
2018	288	45	13	28.88%
2019	351	62	25	40.32%
2020	123	25	7	28.00%
2016-2020	1197	219	74	33.79%

*Number of announcements analysed during the period. **Number of the significant announcements that were classified statistically significant at 1% level. ***Number of the announcements for which APAVs were observed at a statistical significance level of 10%. ****The ratio of SAs that were preceded by APAVs.

The current study’s findings regarding the statistical significance of CAVs around company announcements are reinforced by the empirical findings of Felimban et al. (2018) who investigated the impact of dividend change announcements on trading volume. They observed significant increases in CAVs during the event window, indicating that dividend announcements are highly informative in the GCC market, including the Tadawul. Moreover, the results are consistent with those of Alzahrani and Gregoriou (2010) who present systematic evidence of informed trading before the release of earnings announcements in the Tadawul and of significant abnormal trading activities over the 10 trading days prior to event day. With respect to SAs, the current results align with those of Alhassan et al. (2019) who find that abnormal trading volume during the post-announcement window is greater than in the pre-announcement window.

It can be inferred that the trading volume market cleanliness measures indicate that the level of possible insider trading in the Tadawul has declined since the adoption of financial reforms. These findings correspond to those of Alhassan et al. (2019), which indicate that information leakage and the occurrence of insider trading in the Tadawul has decreased to some extent because of initiatives undertaken by the CMA to enhance the regulatory environment. However, the key point is whether the observed decrease in the period following the introduction of financial reforms in the current study is statistically significant compared with the previous period. This enquiry relates to the sixth objective as addressed in Section 7.2.6.

The study also sought to investigate the relationship between the MCMs in the return and volume analyses. Based on the literature review in Chapter 4, this investigation aimed to identify any relationship between increases in stock prices and rises in trading volumes prior to announcements. Thus, the study asked the following:

RQ_7. Is there a relationship between the MCMs of the return and volume analysis wherein the SAs that were accompanied by APPMs were also accompanied by APAVs?

To address RQ_7, the study tested the following hypothesis:

H_{09}: There is no significant relationship between the MCMs for return and volume analyses where SAs that were accompanied by APPMs were not also accompanied by APAVs.

To test H_{09}, a cross-tabulation in matrix format was performed (see Table 6.27 for pre-reform period data and Table 6.28 for post-reform period data), which presents the number of events in four categories as follows. The first category includes the count of announcements that had occurrences of both APPMs and APAVs. The second group is comprised of the number of announcements that exhibited APPMs but not APAVs. The third group is announcements that had cases of APAVs but not APPMs. The remaining number constitutes the fourth group which is made up of announcements preceded by neither APPMs nor APAVs. To test H_{09}, a chi-square test of independence was used to verify whether the categories were likely to be related. In regard to RQ_7, the test failed to reject the null hypothesis (p = 0.035) and (p = 0.012) for the pre-reform and post-reforms sample, respectively.

When considering these findings alongside those of relevant studies, there is mixed evidence about the relationship between stock returns and trading volumes. Although Medeiros and Doornik (2008) and Akpansung & Gidigbi (2015) do not report a correlation between trading volume and returns, Gupta et al. (2018) and Chuang et al. (2012) document a relationship between trading volume and returns. Additionally, Al Samman and Al-Jafari (2015) find stock returns to be positively and significantly impacted by trading volume. These findings therefore support the interpretation of announcements preceded by both APPMs and APAVs. Miseman (2019) discover that trading volume has a significant ability to predict stock returns. Alhussayen (2022) finds that trading volume is incapable of conveying information into prices and has no impact on price movements in the Tadawul. These findings back the observations of the second and third group, which relate to announcements that had cases of APAVs but not APPMs, and vice versa, respectively. In the context of previous market cleanliness studies, the current findings are similar to those of Monteiro et al. (2007). In their analysis of a takeover sample, they find that out of 131 announcements, 56 were identified as both APPMs and APAVs whereas 75 were APPMs but not APAVs.

7.2.5 Findings and Discussion Relating to the Fifth Objective: Market Cleanliness Measures of Return

The fifth objective of this study was to evaluate the influence of financial reforms on the level of potential insider trading in the Tadawul based on a comparison of the differences in the returns event study of MCMs before and after the introduction of reforms. This objective led to proposing of the first MRQ:

MRQ$_1$. Is the level of potential insider trading assessed by the MCMs of returns event study significantly lower after the introduction of financial reforms?

To address this question, this study developed the first main hypothesis, which is formulated in a null form, as follows:

MH_{01}: The level of potential insider trading of the returns event study MCMs is not significantly lower after the introduction of financial reforms.

Based on the data presented in Table 7.1, which relate to the findings obtained from MM approach, and those in Table 7.2 derived from the ADL-GARCH approach, the findings indicate that the Tadawul's MCMs for the post-reform period was lower than that for the preceding period. However, to verify MH_{01} and establish the statistical significance of the observed drop, a statistical test of the difference in the ratio of APPMs between the two periods was performed using the *z*-test described in Equation (6.1). Table 7.4 presents the difference between the MCMs for the post- and pre-reform periods according to both methods.

Table 7.4

The Test Statistics for the Difference in MCMs between the Pre- and Post-reform Periods According to the MM and ADL-GARCH Approaches.

Panel A: The Tadawul's market cleanliness measure according to MM approach				
Period	**SAs**	**APPMs**	**Measure**	**Difference**
Pre-financial reforms	55	31	56.36%	11.16%

Post-financial reforms	73	33	45.20%	**(p-value=0.109)**

Panel B: The Tadawul's market cleanliness measure according to ADL-GARCH approach

Period	**SAs**	**APPMs**	**Measure**	Difference
Pre-financial reforms	76	22	28.94%	4.55%
Post-financial reforms	123	30	24.39%	**(p-value=0.264)**

The conclusions reached from both approaches were as follows. Although the Tadawul's MCMs in the returns analysis suggested a drop in the level of potential insider trading after the introduction of financial reforms—by 11.16% and 4.55% as per the MM and the ADL-GARCH approaches, respectively—the statistics show that the observed reduction was not statistically significant. The tests did not permit rejection of the null hypothesis ($z = 1.232$, $p = 0.109$ for the MM approach; $z = 0.629$, $p = 0.264$ for the ADL-GARCH approach) because the difference shown by a decline in the MCMs following the post-reform period lacks statistical significance.

As for the findings pertains to the notable decrease in MCMs, the results of the current study are consistent with those reported by Alhassan et al. (2019) who indicate that there has been a decline in information leakage and insider trading in the Tadawul because of the implementation of regulations by the CMA to enhance the information environment. On the other hand, the absence of statistically significant changes in MCMs can be attributed to the evidence from the academic literature which demonstrate that it is the rigorous implementation of enforcement measures, rather than simply the introduction of laws, that results in a positive meaningful impact (Bhattacharya & Daouk, 2009; Chen et al., 2017; Cline et al., 2021; Kwabi et al., 2018).

7.2.6 Findings and Discussion Relating to the Sixth Objective: Market Cleanliness Measures of Volume

The sixth objective was to assess whether financial reforms influenced the possible insider trading level in the Tadawul via a comparative analysis of the differences in the volume event study of MCMs before and after the introduction of the financial reforms. This objective prompted the second main research question:

MRQ_2. Is the level of potential insider trading assessed by the MCMs of trading volume event study significantly lower after the introduction of financial reforms?

To address this question, the study formulated its second main hypothesis in the form of a null statement, as follows:

MH_{02}: The level of potential insider trading of the trading volume event study of MCMs is not significantly lower after the introduction of financial reforms**.**

The data reported in Table 7.3 in Section 7.2.4 show that there were 63 instances of APAVs observed prior to a total of 155 SAs and that 219 SAs were preceded by 74 cases of APAVs over the pre- and post-reform periods, respectively. The findings suggest that the VMCMs of the volume event study analysis of the pre-reform period was estimated at 40.65% and for the post-reform period stands at 33.79% showing a decrease of 6.86% compared with the preceding period.

To test MH_{02} and assess the statistical significance of the observed decline, a statistical test was conducted to assess the difference in the VMCMs between the two periods. This involved utilisation of the *z*-test shown in Equation (6.1). Table 7.5 shows the difference in the VMCMs between the pre- and post-reform period.

Table 7.5

The Test Statistics for the Difference in VMCMs Between the Pre- and Post-reform Periods.

Period	Sas	APAVs	Measure	Difference
pre-financial reforms	155	63	40.65%	6.86% **(p-value=0.087)**
post-financial reforms	219	74	33.79%	

The volume analysis led to the conclusion that the Tadawul's VMCMs experienced reduced potential insider trading by 6.86% after the financial reforms were passed. Thus, the hypothesis testing permitted rejection of the null ($z = 1.357$, $p = 0.087$) because the VMCMs for the subsequent period was significantly lower than that for the preceding period.

The results of the quantitative analyses of market cleanliness in the returns and volumes event studies reinforced each other by providing supportive evidence of a decline in the level of potential insider trading activities in the Tadawul after the financial reforms were instituted. However, the return analysis concludes that the observed decrease was not statistically significant. This may be because of insufficient monetary penalties or weak sanctions. The low quality of institutions, weak enforcement of insider trading laws, and minimal penalties and sanctions could create space for insiders to engage in market misconduct (Dalko & Wang, 2016; La Porta. Et al., 2006; Ojah et al., 2020; Porta et al., 1998; Zhang & Zhang, 2018). The CRSD by the end of 2014 had not imposed incarceration for insider trading other than in one instance, where the sentence was for only three months out of a possible five years (Alkhaldi, 2016).

Sharif (2019) suggests that the limited progress in the Tadawul over the post period may be due to weaknesses in laws concerned with protection of investors. Similarly, Bajaher et al. (2022) indicate that the amendments made to governance and capital market regulations in Saudi Arabia may not be sufficient to induce international institutional investment. Algaeed (2021) note that the Saudi capital market's performance, in terms of contribution and promotion to economic development, remains below expectations. These findings may explain the insignificant difference in MCMs since the financial reforms were introduced.

With respect to monetary penalties, Table 2.2 provided in Chapter 2 shows the number of finalised insider trading violation cases and the sanctions imposed by authorities during 2011–2020. The table shows that 111 instances of insider trading were settled over this decade, with financial fines surpassing 352 million SAR. Of these 111 adjudicated cases, 33 were resolved during the pre-reform period and 78 post-reform; thus, more cases of insider trading have been assessed by the regulatory body since the introduction of financial reforms.

These cases data, obtained from the CMA’s annual reports, may help explain the findings of the current study with respect to the absence of significant changes in the MCMs following the implementation of financial reforms. Since there had been more cases in the post-reform era, this lends credence to the current study's conclusions about the lack of a statistically significant decline of the MCMs of return analysis during post-reform period. It is important to note that this study covered the periods before and after the entry of foreign investors, and market reaction and investor behaviour might differ between these periods. Further interpretation can be attributed to the time taken in prosecution procedures for illegal insider trading, which may be lengthy. Thus, it may be premature to make definitive judgements regarding the effectiveness of enforcement in deterring such activities. An additional possible explanation for the lack of a significant change in the MCMs is that recent regulatory changes implemented as a result of financial reforms may not yet have had a substantial impact in diminishing the extent of insider trading activities.

7.3 Implications of the Study

In view of the significance of market integrity and fairness, it is important to identify the consequences of impairments to market integrity and insufficient deterrence of insider trading. Confidence and transparency can foster investor participation, contribute to liquidity, drive more competitive pricing and reduce capital costs. Financial markets can then play a vital role in an economy’s growth and prosperity by enabling investors to cultivate capital and allocate resources and risks effectively.

The conclusions presented in this chapter demonstrate that although the Tadawul’s MCMs provided evidence of advances to some extent, as indicated by a decrease in the occurrence of possible insider trading following the implementation of financial reforms. The empirical evidence provided by this study can be considered by all parties concerned with illegal insider trading and is of major importance to the financial regulator in the Saudi capital market.

First, this study is important for the regulatory body in the Saudi capital market whose mandate is to ensure an effective regulatory regime alongside strict enforcement of regulations against violators of laws. Revisions to the Tadawul securities legislation and regulations relating to insider trading are recommended. The authority bears the responsibility of establishing and maintaining effective monitoring measures to oversee the flow of sensitive information through appropriate channels with accuracy and timeliness. On one hand, ensuring efficient surveillance, transparency and enforcement measures are crucial factors that contribute to enhance market performance, combat the risks associated with market abuses and foster investor confidence as well as protecting them against potential harm caused by market misconduct, including illegal insider trading. On the other hand, weak regulatory performance could lead to a lack of confidence among investors which in turn leads them to reduce their participation in the market with a consequent impact on stock market development.

Second, the study provides a foundation for tracking the deterrent impact of the new regulations in a regulatory setting in relation to insider trading activities and corporate disclosure. Thus, the study findings can be used to evaluate the effectiveness of regulations and enforcement and to determine whether additional regulations are required to improve regulatory performance and deter market abuse. Moreover, it is essential that the public be made aware of illegal practices in the market. Bringing these issues to the attention of the public should not be overlooked by the regulatory body. The significance of public messaging in the context of credible deterrence lies in its ability to effectively convey the message that there are real repercussions for anyone involved in or considering involvement in market abuse (IOSC, 2015).

Third, the results of the study serve as a reminder to companies to abide by rules set forth by the CML and its implementing regulations to strictly control and regulate the release of confidential information by authorised means. Fourth, the results may be beneficial for foreign and domestic investors considering investing in the Tadawul. The findings provide an overview of market integrity and fairness, enhancing investors comprehension through the provision of valuable insights into market conditions and risks.

7.4 Limitations and Recommendations for Future Studies

Although the use of an event study market cleanliness methodology has provided an important estimate of the extent of the presence of insider trading activities in the Tadawul, it is worth pointing out that the study is not free of limitations. First, the method is not intended to serve as a comprehensive approach to identifying the possible effects of other forms of market misconduct. Instead, it specifically focuses on the examination of potential insider trading activities. In future analyses, it is advisable to consider the utilisation of pertinent proxies for instances of other market abuses such as manipulation and spreading rumours or disinformation to artificially increase or decrease security price, to investigate their potential effects on the behaviour of security prices and trading volumes.

Second, the studies reviewed in Chapter 3 and 4 consider the occurrence of APPMs and APAVs ahead of corporate news as an indicator of insider trading and information leakage. Thus, the foundation of the analysis carried out in this research rests on its examination of SAs that were preceded by APPMs or APAVs, which are more likely to be the result of activities involving insider trading. However, it is important to note that the empirical evidence provided refers to potential, not confirmed cases of insider trading. The study does not claim that the detected APPMs and APAVs could have arisen only through insider trading; instead, they are prudently referred to in this thesis as ‘potential’, not ‘actual’ instances of insider trading.

Further justification for the above statement includes that, to the best of the author’s knowledge, evidence of confirmed illegal insider trading cases is predominantly handled by the authorities and judicial regulatory actions.[50] According to Ahern (2017), ‘Though many papers infer the presence of insider trading before corporate announcements based on price and volume run-ups … there is almost no evidence based on direct observations of insider trading’ (p. 42). The author points out that ‘the exceptions are Meulbroek (1992) which studies 183 insider trading events from the 1980s, Cornell and Sirri (1992) which studies one event from 1982, and Chakravarty and McConnell (1999) which studies one case from 1984’. (p. 42). This thesis references previous studies, including Ahern (2017) and Bolandnazar et al. (2020), that have also examined insider trading instances using firsthand observations.

Moreover, it is worth noting that the method may not necessarily detect all instances of insider trading because of other factors that may impact stock prices or trading volumes. For example, individuals with insider knowledge may possess a heightened awareness of the optimal timing for executing their trades in a smart manner. It is pointed out in Chapter 3 that academic studies have extensively examined the proficiency of insider traders in concealing their activities through use of various strategic tactics by timing their trades in relation to the event date (Davis et al., 2020; Katselas, 2019; Kyle, 1985; Suk & Wang, 2021); gradually executing stock purchases or sales to minimise the impact on stock price movements (Ahern 2020; Collin & Fos, 2015); utilising automatic trading when public disclosure is not imminent (Baruch et al., 2017; Collin & Fos 2016); conducting more trades when the event is imminent (Bolandnazar et al., 2020); and spreading trades over a longer time horizon when

[50] Section (3.2) has clearly discussed the findings of previous studies that rely on the direct data collected from regulatory authorities and provide empirical evidence of the impact of insider trading activities on the process of security price formation.

possessing longer-lived information and engaging in shorter-term trading when their informational advantage is short lived (Biggerstaff et al., 2020).

The third limitation pertains to the event window length. Although this study utilised several event window lengths in the price analysis, future studies might consider using more event windows with different sizes in the analysis of trading volumes. Such work may advance our understanding of the potential effects of the event window length on the market cleanliness measures in trading volume analyses. In addition, using different positions for the event window, such as moving it a few days prior to the event day rather than immediately preceding it, may capture any earlier information leakage because insiders may be more cognisant of camouflage and spread their trades over time.

Fourth, the methodology applied operates under the assumption that there are neither confounding events within the event window nor overlapping events within the estimation window.[51] While this study used an event adjustment procedure (see Section 4.3.2) to handle the effects of overlapping on the estimation of stock returns alongside trading volumes, and ensured that there were no confounding events within the event window by manually collecting firms announcements, future research may consider additional measures to mitigate the possible effects of these issues.

Finally, although the study examined the influence of sample-specific factors on the MCMs in the returns analysis, it did not assess the impact of these factors on trading volume because of scope limitations in this study. Therefore, another direction for future research might be to examine the possible effects of relevant factors on the MCMs in a trading volume analysis.

The above limitations relate mostly to methodological aspects, but it is useful to underscore other limitations and recommendations regarding the data sample. This study

[51] The confounding events relate to a situation in which a corporation discloses multiple important announcements on various days during the event window whereas the disclosure during estimation window pertains to overlapping events.

considered sample selection criteria involving restrictions imposed by data availability (see Section 5.2.3). Additionally, the sample of firms events was restricted to unscheduled announcements.[52] However, the use of extended or different samples might be informative about the extent to which changes in the market reaction may vary with different types of announcements. It could be interesting to compare stock price movements as well as trading volume pattern differences between scheduled and unscheduled announcements.

This research has also identified challenges and cautions pertaining to the task of data collection. The study considered concerns raised in the literature concerning data quality and source. Following a thorough examination of various data sources and identification of certain data discrepancies (see Section 5.2.2), future studies should be mindful of shortcomings with the use of some data sources to verify the absence of any inaccuracies in the compiled data.

Future event studies could ensure that announcements are published during trading hours, as recognised by the current study. Failure to consider the announcement time when determining the event date may result in incorrect identification of the dates for announcements made after trading hours (see Section 5.2.2). It was observed that around 3% of the sampled announcements in the present study were released after the market had closed. Consequently, the subsequent trading day was designated as the event day to ensure that the announcement was made on a day when market participants and stock prices had sufficient time to respond to the subsequent event (Brook, 2019; MacKinly, 1997).

Finally, it is important to remember that the Saudi government made the decision to transition its official weekend to Friday and Saturday, beginning on 29 June 2013. Hence, future research examining the Tadawul stock market with a focus on retrospective analysis

[52] The decision for restricting the sample selection to unscheduled announcements have been extensively justified with reference to other studies in Section 5.2.

dating back to June 2013 should recognise the difference in trading days before and after 29 June 2013.

7.5 Concluding Remarks

A substantial corpus of scholarly literature extensively examines the practice of illegal insider trading and consistently corroborates that the proper functioning of financial markets relies heavily on confidence. However, the exploitation of privileged information undermines this trust, giving rise to apprehension regarding the integrity and fairness of the market.

The amended regulations introduced with the Saudi financial reforms in 2016 were established to ensure fairness in the Tadawul and align market practices with global best standards. However, the rise in criminal prosecutions along with massive penalties imposed by the CMA against those who engage in illegal insider trading activities has raised concerns about the integrity of the Tadawul. Motivated by these observations as well as the lack of research into the estimation of insider trading practice in the Tadawul, this thesis has striven to empirically assess the impact of the regulatory changes introduced with the financial reforms on the level of potential insider trading in the Tadawul by examining market cleanliness in the periods before and after the introduction of financial reforms.

The level of potential insider trading was estimated by employing the event study market cleanliness methodology, which determines the proportion of SAs that were preceded by APPMs and APAVs. The analysis was carried out by conducting return and volume event study methods to gauge the impact of an event on a security return and trading volume using a sample of 1,958 unscheduled announcements made by firms listed in the Tadawul from 2011 to 2020. A range of econometrics models, namely the SLR, GARCH (1,1), ADL (1,1) and ADL-GARCH, were utilised to model ARs and AVs with the aim of evaluating their efficacy, examining their differences and drawing meaningful conclusions.

The findings suggest that the proportions of APPMs and APAVs detected ahead of SAs were lower after the introduction of financial reforms. The Tadawul's MCMs for the returns event study analysis according to the MM approach showed that 56.36% of SAs were preceded by APPMs across the pre-reform period compared with 45.2% after financial reforms were passed. The ADL-GARCH approach estimated the returns event study MCMs of the Tadawul at 28.94% and 24.39% for the pre- and post-reform periods, respectively. The trading volume analysis showed that the MCMs for the Tadawul was 40.65% during the first period and 33.79% over the second period. A further robustness check examined the possible effects of event window size as well as ensuring that the study findings regarding MCMs were not driven by other factors using the logistic regression, the results show that none of other factors, with exception to trading activity factor, have had significant impact on the MCMs.

The conclusions drawn from this research were as follows. All analyses of event study market cleanliness measures for the Tadawul provided empirical evidence of improvements in the market integrity as evidenced by reduction in the level of potential insider trading in the Tadawul after financial reforms were passed. However, the returns event study MCMs indicated that the statistics for the subsequent period were not significantly lower than the preceding period. Nevertheless, the trading volume analysis indicated that the reduction in level of potential insider trading was statistically significant at 10% following the introduction of financial reforms. A possible explanation for the lack of significance in the returns MCMs is that the regulatory changes introduced with the financial reforms have not yet had a significant impact in reducing the level of potential insider trading activities in the Tadawul. Further, the lack of significance may be attributed to evidence from previous academic research that it is the stringent implementation of enforcement mechanisms, rather than merely introduction of legislation, that leads to a statistically significant impact.

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