Stock Selection for Trading Strategies Based on Risk Factors: A Study of The Ho Chi Minh Stock Exchange

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Thesis submitted in fulfillment of the requirement for the degree of Doctor of Philosophy (Integrated)

College of Business, Victoria University

Institute for Sustainable Industries and Liveable Cities

2023

Abstract

This research focuses on stock selections for trading strategies based on cross-sections of stock returns and risk factors in the Ho Chi Minh Stock Exchange (HSX), an emerging market. To select the right stocks for trading strategies, this thesis is divided into three steps. First, I analyse different characteristics that affect stock returns with new ones: dynamic beta, Value-at-Risk (VaR), and conditional Value-at-Risk (CVaR); and traditional ones: static beta, firm size, firm value, momentum, and illiquidity. This study uses different regression models on sample panel data in the HSX. For dealing with heteroskedasticity, different robustness techniques, including the traditional Newey–West method (when the residuals are correlated across time) and new clustering techniques (when the residuals are correlated across firms or across time, or across both firms and time) (Millo, 2019; Petersen, 2009) are used to reduce biases in testing the effect of the above characteristics on stock returns. Second, I study different available risk factors such as market, size, value, momentum, profitability, investment, illiquidity, Value-at-Risk, and develop a new factor called conditional Value-at-Risk. The GRS test (Gibbons et al., 1989) is applied to determine the appropriate risk model for this market.

The final part of this thesis tests stock selection strategies based on understanding factors that affect stock returns. The performance of strategies is evaluated by a non-parametric test using a t-test and a parametric test using alpha (the intercept of the selected risk factor model). If the alpha of a strategy is positive, this strategy outperforms the market (the return of the strategy is higher than that of the selected risk factor model), and investors can apply it for their trading. If this strategy underperforms the market (the return of the strategy is lower than that of the selected risk factor model), investors can reject it. If the alpha is zero, the return of a strategy is predicted by the market (the return of the strategy is indifferent from that of the selected risk factor model).

The first study found that double clustering panel regressions are more appropriate than OLS, between-estimator, and Fama–MacBeth regressions for coefficient estimations because both individual and time effects exist in the errors (Petersen, 2009; Sun et al., 2018). Furthermore, based on the Hausman test (Croissant & Millo, 2018), the fixed-effect models are preferred to the random-effect models. These models indicate that stock returns are positively and significantly correlated with momentum and dynamic beta but negatively correlated with firm size.

The second study found that different combinations of risk factors can explain stock returns in the HSX. However, the GRS test shows that the three-factor model (containing the market, size, and investment factors) performs better than other multifactor models. The last study found that both long and arbitrage strategies earn positive returns and positive alphas. In particular, buying small-size stocks in the high Value-at-Risk (SHVaR portfolio) outperforms the market, and this strategy generates the highest return (approximately 2.38% monthly) compared to other strategies. This implies that the HSX is not efficient and recommended strategies in this thesis should help investors earn positive returns. The results of this thesis provide practical insights. First, policymakers can utilize the risk factors to evaluate the efficiency of the market. Second, investors can select stocks for their portfolios based on the correlation between stock returns and their characteristics. Last, investors can select the best risk model to evaluate if their investment strategies earn higher returns than that of the market required.

Declaration

I, Hoang Thach Pham, declare that the PhD thesis entitled "Stock Selection for Trading Strategies Based on Risk Factor: A Study of the Ho Chi Minh Stock Exchange" is no more than 80,000 words in length including quotes and exclusive tables, figures, and references. 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 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]

Hoang Thach Pham

Dedication

This thesis is dedicated to my beloved parents who encouraged and pushed me on the right path, not only in my academic career, but also throughout my life. This thesis is also dedicated to my lovely wife, my son, and my daughter who motivated me since the beginning of my studies. I owe all the moments of my life to them and appreciate their love, compassion, and encouragement.

Acknowledgments

I would like to express my gratitude to my principal supervisor, Dr Guneratne Wickremasinghe, and my associate supervisor, Associate Professor Nada Kulendran, for their advice and encouragement. This dissertation would not have been possible without their support, guidance, and expertise in this field. Furthermore, I am grateful to Victoria University, especially the Business School, the Institute for Sustainable Industries and Liveable Cities**,** for accepting me to their integrated PhD program. I am also thankful to librarians and other staff at Victoria University who help me develop my research skills through workshops and learning hubs. They also guide me to use the Eikon database to collect data for my thesis. In addition, I appreciate R Core Team and the Comprehensive R Archive Network for providing statistical computing and graphics. Moreover, I would like to thank the Vietnamese Government and Victoria University for providing me with a scholarship to pursue my doctoral studies. Also, my gratitude goes to all my friends and colleagues at the Ho Chi Minh City Open University who continuously cared for and motivated me during the time I pursued this degree.

I also acknowledge the services of Sarah Endacott, of edit or die, who performed copy-editing and formatting on this document, according to the principles and standards of the Australian Institute of Professional Editors (IPEd).

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Acronyms and Abbreviations

3FM	three-factor model
4FM	four-factor model
5FM	five-factor model
ADF	Augmented Dickey–Fuller test
AMEA	Europe, the Middle East and Africa
AMEX	American Stock Exchange
APT	arbitrage pricing theory
ASEAN	Association of Southeast Asian Nations
ATC	at the close order
ATO	at the open order
BD	big-size and down (low)-momentum portfolio
BE	between estimation
BG	Breusch–Godfrey test
BH	big-size and high-value portfolio
BHCAPM	big-size and high-CAPM beta portfolio
BHCVaR	big-size and high-CVaR portfolio
BHDCC	big-size and high-DCC beta portfolio
BHIlliq	big-size and high-illiquidity portfolio
BHVaR	big-size and high-VaR portfolio
BL	big-size and small-value portfolio
BLCAPM	big-size and low-CAPM beta portfolio
BLCVaR	big-size and low-CVaR portfolio
BLDCC	big-size and low-DCC beta portfolio
BLIlliq	big-size and low-illiquidity portfolio
BLVaR	big-size and low-VaR portfolio
BM	big-size and medium-value portfolio
BMCAPM	big-size and medium-CAPM beta portfolio
BMCVaR	big-size and medium-CVaR portfolio
BMDCC	big-size and medium-DCC beta portfolio
BMIlliq	big-size and medium-illiquidity portfolio
BMVaR	big-size and medium-VaR portfolio
BN	big-size and neutral (medium)-momentum portfolio
BP	Breusch–Pagan test
BRIC	Brazil, Russia, India, China, and South Africa
BSE	Bombay Stock Exchange
BTM	book-to-market equity ratio

BU	big-size and up (high)-momentum portfolio
BV	book value
C/P	cashflow-to-price ratio
CAPM	capital asset pricing model
CCAPM	consumption CAPM
CCC	constant conditional correlation
CCM	Chinese Capital Market
CD	cross-sectional dependence test
CMA	conservative-investment minus aggressive-investment
COGS	cost of goods sold
CRSP	Center for Research in Security Prices
CVaR	conditional Value-at-Risk
D/Y	dividend yield
D	Dow (low)-momentum portfolio
DCC	dynamic conditional correlation
E/P	earning-to-price ratio
FE	fixed effects
FM	Fama–MacBeth regression
GARCH	generalised autoregressive conditional heteroscedasticity
GCC	Gulf council countries
GRS	Gibbons, Ross, & Shanken test
H, M, L	high (medium/low) value
HCAPM	high-CAPM beta portfolio
HCVaR	high-CVaR portfolio
HDCC	high-DCC beta portfolio
HIlliq	high-illiquidity portfolio
HILLIQL	high-illiquidity minus low-illiquidity
HML	high-value minus low-value
HNX	Hanoi Stock Exchange
HSX	Ho Chi Minh Stock Exchange
HVaR	high-VaR portfolio
HVaRL	high-VaR minus low-VaR
I	investment
ICAPM	intertemporal CAPM
IE	interest expense
IFC	international financial corporation
JB	Jarque–Bera test
KSE	Karachi Stock Exchange

LCAPM	low-CAPM beta portfolio
LCVaR	low-CVaR portfolio
LCVaRH	low CVaR minus high CVaR
LDCC	low-DCC beta portfolio
LIlliq	low-illiquidity portfolio
LLC	Levin–Lin–Chu test
Ln	natural logarithm
LO	limit order
LVaR	low-VaR portfolio
MAK	match and kill order
MCAPM	medium-CAPM beta portfolio
MCVaR	medium-CVaR portfolio
MDCC	medium-DCC beta portfolio
MIlliq	medium-illiquidity portfolio
MKT	market portfolio
MoF	Ministry of Finance
MOK	match or kill order
MP	market price order
MRS	Markov regime-switching
MTL	market to limit order
MV	market value
MVaR	medium-VaR portfolio
N	neutral (medium)-momentum portfolio
NASDAQ	National Association of Securities Dealers Automated Quotations System
NIFTY 200	Market Index of 200 Large and Mid Market Capitalisation Companies (India)
NSE	National Stock Exchange (India)
NYSE	New York Stock Exchange
OLS	ordinary least squares
OP	operating profit
P/B	price-to-book equity ratio
PCD	Pesaran CD test
PLO	post limit order
Q-Q	quantile-quantile plot
RE	random effects
RMW	robust-profitability minus weak-profitability
S, M, B	small (medium/ big) size
SD	small-size and down (low)-momentum portfolio
SGA	selling, general, and administrative expenses

SH	small-size and high-value portfolio
SHCAPM	small-size and high-CAPM beta portfolio
SHCVaR	small-size and high-CVaR portfolio
SHDCC	small-size and high-DCC beta portfolio
SHIlliq	small-size and high-illiquidity portfolio
SHVaR	small-size and high-VaR portfolio
SL	small-size and small-Value portfolio
SLCAPM	small-size and low-CAPM beta portfolio
SLCVaR	small-size and low-CVaR portfolio
SLDCC	small-size and low-DCC beta portfolio
SLIlliq	small-size and low-illiquidity portfolio
SLVaR	small-size and low-VaR portfolio
SM	small-size and medium-value portfolio
SMB	small-size minus big-size
SMCAPM	small-size and medium-CAPM beta portfolio
SMCVaR	small-size and medium-CVaR portfolio
SMDCC	small-size and medium-DCC beta portfolio
SMIlliq	small-size and medium-illiquidity portfolio
SMVaR	small-size and medium-VaR portfolio
SN	small-size and neutral (medium)-momentum portfolio
SSC	state securities commission
SU	small-size and up (high)-momentum portfolio
TA	total assets
U	up (high)-momentum portfolio
UMD	up-momentum minus down-momentum
UPCOM	unlisted public company market
VaR	Value-at-Risk
VIF	variance inflation factor
VSD	Vietnam Securities Depository

Chapter 1: Introduction

1.1. Introduction

This thesis develops a framework that not only helps in explaining stock returns but also provides profitable trading strategies. Because of the differences in market structures between developing and developed markets and the decline of publicised risk factors (Hanauer & Lauterbach, 2019; Jacobs & Müller, 2020; Ragab et al., 2020), this research contributes to reconstructing those factors, and developing a new one called LCVaRH to improve the efficiency of existing risk models. Furthermore, this thesis tests different risk factors on the Ho Chi Minh Stock Exchange (HSX) in Vietnam, a developing market. This provides an out-of-sample test for the literature because most of the tests are conducted on developed markets (Fama & French, 2017; Hanauer & Lauterbach, 2019; Wang et al., 2021). Moreover, the framework developed in this thesis is not just useful for the HSX, but also for other stock markets.

This research focuses on stock selection for trading strategies based on risk factors in the Ho Chi Minh Stock Exchange (HSX). It studies the risk factors that can explain the fluctuation of stock returns in the HSX. The thesis is also based on the relationship between risks and returns to select stocks into different portfolios for trading. This study combines both risk factors in stock and portfolio levels in this market. Understanding risk factors that affect stock price fluctuations or stock returns is crucial. It helps not only investors and financial institutions to make their trading decisions, but it also helps authorities to provide appropriate legislation for the development of the stock market. First, the research examines the cross-sections of stock returns and their risks (firm levels). Second, it examines risk factors (portfolio levels) to create equilibrium models for this market. All factors are reconstructed by using single sort rather than double sorts such as the Fama and French approach (Fama & French, 1993; 2015). This simplifies the calculation; however, it will also increase the power of portfolios, especially in small samples in emerging markets. Then, based on the understanding of the cross-section of stock returns, different stock selection strategies are formed to look for positive returns. Different quantitative methods, including parametric and nonparametric techniques, are adopted to test trading strategies on the HSX.

Previous studies have used common risks such as the size factor (SMB), value factor (HML), momentum factor (UMD) (Cakici et al., 2013; Cakici et al., 2016; Carhart, 1997; Fama & French, 1993; 2015; Hanauer & Linhart, 2015) or characteristic risks (firm characteristics) such as stock betas, market capitalisation, book-to-market equity, momentum (Fama & French, 1992; Hanauer & Lauterbach, 2019; Jegadeesh & Titman, 1993; van der Hart et al., 2005; 2003; Zaremba & Konieczka, 2015) to study the cross-section of stock returns. Common factors are viewed as common sources of risk, while characteristic factors are specific risks related to an asset (Harvey & Liu, 2019; Harvey et al., 2016). This thesis examines both characteristic risks and common risks to explain stock returns. Both risks help investors understand the relation between stock returns and those risks; therefore, they have opportunities to select the right stocks to buy or sell. In addition, the factor models using common risks can be used to evaluate the performance of portfolios that investors hold. Thus, the combination of both studies can help researchers to explain stock returns and give investors a tool to evaluate their investment performance. Based on understanding the cross-section of stock returns and pricing errors (measured by Jensen's alphas of common risk factor models), this thesis proposes appropriate stock selection procedures and trading strategies that earn positive excess returns.

1.2. Research Problem

Previous studies have focused on the well-known factors in the literature, such as the market model, the three-factor model, and the four-factor model to trace alphas without testing if they are appropriate to a particular market structure (Hanauer & Lauterbach, 2019; van der Hart et al., 2005; 2003). This research recommends that the factor models should be tested before they are used due to the differences in market structures (Drew & Veeraraghavan, 2002; Ragab et al., 2020) and the decline of publicised factors (Jacobs & Müller, 2020; Mclean & Pontiff, 2016). Many factor models are tested in the US (home bias) or developed markets outside the US (foreign bias) (Hanauer & Lauterbach, 2019). Therefore, these models may not be appropriate for developing countries because of the differences in market structures. Jacobs and Müller (2020) and Mclean and Pontiff (2016) found that the declining importance of factors may be caused by the publication of factors. Mclean and Pontiff (2016) explain that investors can learn about mispricing from journal articles. These authors state that publication could cause more arbitrageurs to trade on the factors constructed in the literature. This leads to the returns related to those factors that should disappear, or at least decay after the paper is published. In addition, because the effects of old models reduce over time in explaining stock returns (Fama & French, 2012; 2015; Jacobs & Müller, 2020; Mclean & Pontiff, 2016), there is a need to use new models in studying the factors affecting stock returns.

A large number of factors are constructed to explain stock returns (Cochrane, 2011; Harvey et al., 2016). Lo and MacKinlay (1990) are sceptical that factors in asset pricing models are merely data snooping or statistical artifacts. To solve this problem, evidence from different markets and different sample periods are used to corroborate (Aziz & Ansari, 2017). Aziz and Ansari (2017) recommend testing factor models in different markets and different sample periods to verify the effects of these models. Hanauer and Lauterbach (2019) state that emerging market samples should be used to test empirical asset pricing to avoid “home bias” (US market) and “foreign bias” (developed markets outside the US). These new sample tests can answer if factors found in developed countries are due to data snooping (Hanauer & Lauterbach, 2019). Factor models are significant because they are backed by the arbitrage pricing theory (APT). Many papers use factor models to explain stock returns and those models are used to find the appropriate portfolios to invest in because of mispricing (Fama & French, 1998; 2012; Hanauer & Lauterbach, 2019; Harvey et al., 2016; van der Hart et al., 2005; 2003). Thus, testing factor models using data in developing countries is considered out-of-sample tests to the literature according to the recommendation of Hanauer and Lauterbach (2019).

The two-step cross-sectional regression developed by Fama and MacBeth (1973) is widely adopted in finance literature (Harvey et al., 2016; Jagannathan & Wang, 2002). This method estimates parameters based on panel data using the ordinary least squares regression (OLS) (Fama & MacBeth, 1973; Millo, 2017; 2019; Petersen, 2009). Because betas of stocks are estimated using historical data, they have sampling errors. This is the limitation that is called “errors-in-the-variables” when applying Fama–MacBeth regression (Bhandari, 1988; Claessens et al., 1995; Jagannathan & Wang, 2002). Claessens et al. (1995) state that the “between-estimator technique” can decrease this error by the averaging process. This technique takes the average of the data before running the OLS and it can capture the cross-sectional information in the data (Claessens et al., 1995; Croissant & Millo, 2018). In addition, Petersen (2009) states that Fama–MacBeth regression developed by Fama and MacBeth (1973) only solves a time effect, but an individual effect or both effects. Recently, with the development of panel regressions and clustering techniques, standard errors of coefficients can be corrected by cross-sectional correlation, serial correlation, or both correlations (Millo, 2019; Petersen, 2009; Sun et al., 2018; Thompson, 2011). Therefore, panel regressions with clustering robustness can provide better results for panel data. Although tests in asset pricing widely use panel data, robust panel regressions using clustering techniques are limited in use (Fama, 2014). Grouping data into predetermined portfolios also can help to reduce measurement errors (Gibbons et al., 1989; Jagannathan & Wang, 2002). This adoption is used in common risk studies (Bali & Cakici, 2004; Carhart, 1997; Fama & French, 1993; 2015). This thesis compares different regression models: OLS, Fama–MacBeth, between estimators, and panel data regressions to test whether new panel regressions improved the shortcoming of old models.

1.3. Aims

This research has three aims:

1) estimating the relation between stock returns and characteristics risks using the data from the HSX

2) developing common risk factors using a single sort variable and testing the appropriateness of different factor models for this market

3) formulating stock selection for trading strategies based on the Jensen's alphas (the intercepts of factor models) for this market.

These studies are critical for both improving the understanding of the market and building stock trading strategies on the HSX. For example, in finance theory, the CAPM state that stock returns are linearly and positively correlated with their beta. If this statement is true, investors should buy stocks with high beta and sell stocks with low beta. The explanations of the three aims are below.

The first aim studies the effects of different characteristic risks on stock returns, including both popular anomalies such as static beta, size, value, and momentum (Fama & French, 1992; Jegadeesh & Titman, 1993), and newer anomalies including dynamic betas (Bali et al., 2017; Engle, 2002), illiquidity (Amihud, 2002; Chen et al., 2019), Value-at-Risk (VaR) (Aziz & Ansari, 2017; Bali & Cakici, 2004), and conditional Value-at-Risk (Abad et al., 2014; Ling & Cao, 2020). This study uses panel data with different methodologies, including the Fama–MacBeth regression, the between-estimator technique, and panel regression. The Fama–MacBeth regression is popular in the literature in this field while the between-estimator and panel regressions are studied to improve the limitation of the Fama-MacBeth technique (Bhandari, 1988; Claessens et al., 1995; Fama, 2014; Sun et al., 2018).

The second aim is to develop common risk factors for the HSX. Portfolios are constructed to represent common risk factors, including: market portfolio (MKT); small size minus big size (SMB); high value minus low value (HML); up momentum minus down momentum (UMD); high illiquidity minus low illiquidity (HILLIQL); high Value-at-Risk minus low Value-at-Risk (HVaRL); low conditional Value-at-Risk minus high conditional Value-at-Risk (LCVaRH); robust profitability minus weak profitability (RMW); and conservative investment minus aggressive investment (CMA). The proxy for the MKT is the excess market return. Other factors are constructed using long-short portfolios with the median as breakpoints (Bali & Cakici, 2004; Banz, 1981; Harvey et al., 2016). To test the cross-sectional relation, the popular approach is to use 25 portfolios using size quintiles and value quintiles (Bali & Cakici, 2004; Fama & French, 1993). However, the sample of this thesis is small; therefore, the median is used as the breakpoint for size, and 30th and 70th percentiles are used as breakpoints for other variables. In addition, this study expands sample tests by using a different combination of firm size and static beta, firm size and dynamic beta, firm size and firm value, firm size and momentum, firm size and illiquidity, firm size and Value-at-Risk, firm size and conditional Value-at-Risk. Therefore, six portfolios are created for each combination and 42 portfolios are used as the sample test. Different factor models based on common risks are tested and compared before using for evaluating investment performance. The GRS statistic (Gibbons et al., 1989) is used to evaluate the performance of linear factor models (Fama & French, 1993; 1998; 2012; 2015; Jagannathan & Wang, 2002; Skočir & Lončarski, 2018). In addition, the research detects the multicollinearity and stationary of data using correlation matrices, variance inflation factors (VIF), and augmented Dickey-Fuller tests (Wooldridge, 2012) that are lack of in many papers.

The third aim is to formulate stock selection for trading strategies. The performance of stock selection strategies is based on pricing errors called Jensen's alphas of factor models (Fama, 2014; Hanauer & Lauterbach, 2019; Jagannathan & Wang, 2002; Jensen, 1968; van der Hart et al., 2005). All assets are priced correctly by the market when Jensen's alphas are all zeros. Otherwise, assets are mispriced. If Jensen's alphas are positive, portfolios are performing better than the market and investors should buy them. In contrast, those assets are performing worse than the market and they should be sold. The stocks are selected from understanding the cross-sections of stock returns. Jensen's alphas are intercepts of factor models. Stock selection strategies are based on CAPM beta, DCC beta, firm size, firm value, momentum, illiquidity, Value-at-Risk (VaR), and conditional Value-at-Risk (CVaR). Different trading strategies including long and arbitrage strategies are tested using both single and double sorts to search for positive alphas.

1.4. Research Questions

The focal study of this thesis is how to select stocks that bring positive returns for investors in the HSX. The capital asset pricing model (CAPM) (Sharpe, 1964) shows that only market beta is positively correlated with stock returns. Empirical studies found that market beta is insignificant in explaining stock returns; however, other factors can predict stock returns (Fama, 2014; Fama & French, 1993; Harvey & Liu, 2019; Harvey et al., 2016). In addition, while static beta in the CAPM model cannot explain stock returns, the dynamic beta can (Bali et al., 2017; Engle, 2002). Similarly, conditional Value-at-Risk (CVaR) is found more efficient than Value-at-Risk (VaR) because returns are non-normalised (Unbreen & Sohail, 2020; Uryasev, 2000). Therefore, the first study answers the following questions:

- What are the factors that significantly affect the stock returns of the HSX?
- Does the dynamic beta (DCC beta) have a better effect than the static beta (CAPM beta) in explaining stock returns on the HSX?
- Does conditional Value-at-Risk (CVaR) have a better effect than the Value-at-Risk (VaR) in explaining stock return in the HSX?

Next, investors should understand how to measure the performance of their portfolios to evaluate their stock selection strategies and if they bring positive returns. In the literature, researchers have developed multifactor models combined by risk factors as equilibrium models, and the intercepts of these models are used to evaluate the performance of portfolios (Fama, 2014). However, the effects of existing models reduce over time because more arbitrageurs trade on these factors (Jacobs & Müller, 2020). In addition, the economic structures between developing markets and developed markets are different (Ragab et al., 2020). Therefore, researchers need to test which factors can be used as sources of risks before they are used to measure the performance of the investment. Hence, the second study answers the following questions:

- Do the popular three-factor model (Fama & French, 1993), four-factor model (Carhart, 1997), and five-factor model (Fama & French, 2015) explain all the risks in the HSX?

- Are these models improved the efficiency when adding other risk factors?

- What factor models account for the most risk or what models can be used as equilibrium models in the HSX?

Then, the thesis forms different stock selection strategies based on the understanding of the correlation between stock returns and their characteristics in the first study. The performance of these strategies is evaluated by the t-test and the alphas (the intercepts of the factor model in the second study). Therefore, the last study answers the following questions:

- Is the HSX efficient?

- Which stock selection method for trading strategy provide the best portfolio performance in the HSX?

1.5. Contribution to Knowledge and Statement of Significance

1.5.1. Academic Contribution

First, current studies in emerging countries focus on size, value, and momentum (Cakici et al., 2013; Hanauer & Lauterbach, 2019; Hanauer & Linhart, 2015; van der Hart et al., 2005), and the fact that the effects of well-known factors reduce over time (Jacobs & Müller, 2020; Mclean & Pontiff, 2016); hence, studying different factors can improve the efficiency of the model to explain stock returns. This research examines different factor models, including the market model (Sharpe, 1964), three-factor model (Fama & French, 1993), four-factor model (Carhart, 1997), and five-factor model (Fama & French, 2015). Furthermore, this thesis studies the combination of the risk factors in the five-factor model (Fama & French, 2015) with the momentum factor developed by Carhart (1997), the illiquidity, and Value-at-Risk factors developed by Bali and Cakici (2004). This thesis also develops a new risk factor called conditional Value-at-Risk factors based on recent findings that stock return and conditional Value-at-Risk are negatively correlated (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Unbreen & Sohail, 2020; Vo et al., 2019).

The popular approach uses double-sort variables with the median as the breakpoint for size and the 30th and 70th percentiles as breakpoints for other variables to build factors (Carhart, 1997; Fama & French, 1993; 2015). Skočir and Lončarski (2018) show that using many sort variables may cause lower diversification because of the low number of stocks in some portfolios or because there are portfolios without stocks. In other words, reducing breakpoints will increase the number of stocks in each portfolio and increase the power of factors. Thus, the multiple-sort approach is not appropriate for small sample stocks in emerging countries. This thesis uses a single-sort variable and median as the breakpoint to construct common risk factors. This approach is similar to the construction of the HILLIQL and HVaRL using a single sort variable based on illiquidity and Value-at-Risk with the median as the breakpoint for both factors (Bali & Cakici, 2004). Furthermore, Fama and French (1993; 2015) show that the breaks are arbitrary and the performance of models does not depend on the way factors are constructed. Moreover, using more sort variables to form factors is challenging especially for beginners. Therefore, using a single-sort approach is more friendly, especially for teaching and learning this topic.

Previous studies heavily use Fama–MacBeth regression for learning characteristic risks; however, this methodology has an error-in-variables bias (Bhandari, 1988; Claessens et al., 1995). Many variables in this research are estimated from historical data; therefore, they are exposed to measurement errors. Thus, adding the between-estimator technique may reduce the errors of these variables and increase the statistical inference (Claessens et al., 1995). Furthermore, this thesis applies the new clustering techniques for panel regressions that are available at the moment and are known as a better tool for dealing with panel data (Fama, 2014; Sun et al., 2018). Because this approach rarely is used in asset pricing (Fama, 2014), this can give an example for reference of the efficiency of this method compared to the Fama–MacBeth and between-estimator estimations.

Last, according to Karolyi (2016), Hanauer and Lauterbach (2019), studies on financial anomalies are biased by using the US data (home bias) or developed markets outside the US (foreign bias). The economic structures of developed and developing markets are different. In particular, the new stock market in Vietnam, a socialist country, is immature and partly controlled by the government. Thus, this research gives an out-of-sample test by using data in the HSX, an emerging market as recommendations by some scholars (Hanauer & Lauterbach, 2019; Ragab et al., 2020).

1.5.2. Practical Contribution

According to van der Hart et al. (2003), little research has studied individual stock selection for trading strategies especially in emerging countries. In addition, Cao et al. (2013) recommend that more studies on trading strategies based on portfolio selections should be conducted because of their usefulness and practicability. To fill in this gap, this thesis will create trading strategies based on studying the relationship between stock returns and risk factors on the HSX to figure out efficient methods to select stocks into portfolios and earn higher returns.

The research does not just provide a new factor model to the literature, the portfolio buildings provide a powerful tool for long-term investors to evaluate investment performance (Fama & French, 1992). While most of the research in this area has been conducted in the US context, less research has been conducted in developing markets. In addition, not many studies are conducted in the Vietnam stock market. Moreover, previous studies on stock returns in Vietnam are conducted either at stock levels (Batten & Vo, 2014; Pham et al., 2018) or portfolio levels (Hoang & Phan, 2019; Tran et al., 2013), but not both. This thesis will develop a procedure to capture the causal effect of stock returns and their risks (both in stock and portfolio levels) on the HSX. This helps investors, policymakers, and researchers understand what risk factors affect returns in this market. This also helps stakeholders understand market behavior better. For example, investors can utilise the correlation between those risks and asset returns to make better investment decisions. Additionally, some effects which are limited studied in the literature, especially in emerging markets, such as dynamic beta, VaR, and CVaR are conducted in this thesis. Furthermore, when they are added to existing models, they can add new information. For example, if a dynamic beta can capture the risk better than the static beta, the CAPM model can be revived for explaining stock returns (Bali et al., 2017; Engle, 2002). Moreover, the research applies different stock selections in different portfolios to find positive returns and propose winning trading strategies. It should help investors use market data to create equilibrium models and apply these strategies for their trading activities on the HSX to generate higher returns. The methodology developed in this research can be applied to other markets, especially, emerging markets similar to Vietnam.

1.5.3. Statement of Significance

This research is important that not just to give the verification in the Vietnamese market, but also to raise awareness of three issues. First, the Fama–MacBeth regression is biased by measurement errors. In addition, the Fama–MacBeth approach deals with only a time effect. Therefore, other estimations such as between-estimator or panel regressions with clustering robustness may reduce biases and precise coefficients. Second, because the effects of publicised factor models reduce over time, researchers should test them before using or creating new ones. Third, the combination of characteristic risks, common risks, and stock selections can help researchers not only explain stock returns but can also be used as a tool for investment evaluation by tracing alphas.

1.6. Thesis Structure

This thesis consists of eight chapters. Chapter 1 introduces the topic, which represents the research problems, aims, research questions, research contributions, and thesis structure.

Chapter 2 reviews the literature related to studies on the cross-section of stock returns, multifactor models, and appropriate hypotheses for stock selections for trading strategies on the HSX.

Chapter 3 represents the methodology that shows the estimation of stock returns and different firm characteristics using historical trading and financial statements. Different methods measuring the cross-sectional relation between stock returns and firm characteristics are represented: between-estimator, the Fama–MacBeth regression approach, and panel regressions. This chapter also shows the construction of risk factors using a single-sort variable rather than using double-sort variables, and presents the appropriate tests and robustness techniques.

Chapter 4 introduces the Vietnamese stock market and trading regulations in this market. This chapter also represents the statistical summary of sample data containing stock returns, firm characteristics, risk factors, and portfolios for testing the cross-section of stock returns and multifactor models.

Chapter 5 tests the relation between firm characteristics and stock returns. This chapter shows the results of different estimations using between-estimator, the Fama–MacBeth regression approach, and panel regressions to measure the crossectional relation between stock returns in the HSX and their firm characteristics. These models are robust by using the method developed by Newey and West (1987) and clustering techniques.

Chapter 6 tests the multifactor models. This chapter tests different risk factors on the HSX. All risk factors are constructed by using single sort rather than double sorts. The performance of different models is tested by different portfolio samples: Size–Value, Size–Momentum, Size–VaR, Size–CVaR, Size–Illiquidity, Size–CAPM beta, and Size–DCC beta. The GRS test helps to select the best model for the HSX.

Chapter 7 represents stock selection for trading strategies. These strategies are tested both in a single sorting and double sorting to determine what strategies outperform the market. The performance of strategies is tested via the returns and the alphas of long or arbitrage portfolios.

Chapter 8 represents the summaries of the thesis and provides implications for investors and policymakers. This chapter also shows the limitations of this thesis and gives some recommendations for future studies.

Chapter 2: Literature Review

2.1. Introduction

Harvey et al. (2016) review factors that explain stock returns and they have collected over three hundred factors from top journals. These factors are classified into two groups, including common factors (proxies for a common source of risk) (Carhart, 1997; Fama & French, 1993; 2015; Sharpe, 1964) and individual firm characteristic factors (specific to companies) (Ang et al., 2006; Bali et al., 2011; Basu, 1977; Bhandari, 1988). Hanauer and Lauterbach (2019) raise questions about what factors are the best proxies for explaining stock returns and if their power differs across markets. The majority of studies are conducted in developed markets, which causes bias and scepticism on data snooping (Harvey et al., 2016; Karolyi, 2016). Therefore, testing these factors in emerging markets provides new and out-of-sample tests to confirm the effects of these factors and reduce bias and data snooping. Recent studies in emerging markets mainly test the value and momentum effects (Hanauer & Lauterbach, 2019). Hence, many recent anomalies are omitted, such as Value-at-Risk (VaR), conditional Value-at-Risk (CVaR), and dynamic conditional correlation (DCC) beta. Understanding the determinants of stock returns is crucial to selecting the right stocks for portfolio trading.

This chapter presents literature on how to select stocks for portfolios and evaluates the performance of trading strategies. First, the overview of stock selection and trading strategies are represented in Section 2.2. Then, asset pricing theories are reviewed in Section 2.3. This builds a fundamental understanding of how asset returns are explained. Section 2.4 represents the cross-section of firm characteristics and stock returns including betas, size, value, momentum, Value-at-Risk (VaR), conditional Value-at-Risk (CVaR), and illiquidity. Based on the cross-section of stock returns, stocks are grouped in different portfolios and appropriate trading strategies are hypothesised to search for positive returns. Then, common risk factors are surveyed with multifactor models in Section 2.5. These models are not only used to test the efficiency of the market, but also are used to evaluate the performance of the stock selections and related strategies (Fama, 2014; Hanauer & Lauterbach, 2019).

This thesis is different from previous works. First, the tests are conducted in the Ho Chi Minh Stock Exchange (HSX), a developing market and this can avoid the "home bias" and "foreign bias" from those tested in developed markets. Second, this thesis applies different clustering techniques (new developments in econometrics) to robust panel regressions for asset pricing. Third, this thesis develops a new risk factor called LCVaRH based on the conditional Value-at-Risk. Last, this thesis test different trading strategies to find positive returns. Therefore, the results of this thesis not only help policymakers evaluate if the market is efficient, but also help investors make better decisions for their investment by choosing the right strategy that brings the highest returns for their portfolio.

2.2. Stock Selection for Trading Strategies

Cao et al. (2013) state that research on existing strategies in trading agents focuses on the simulation of artificial data. These studies concentrate on mainly developing more accurate mathematical estimation methods and they overlook an important factor: trading strategy. These authors propose an approach called trading strategy-based portfolio selection. This strategy helps trading agents select stocks to construct new portfolios based on the risk appetite of investors. According to van der Hart et al. (2005), stock selection strategies are well documented in developed markets, while only a few papers explore this field in emerging countries. In addition, conflicting results have been found in emerging countries (Claessens et al., 1995; Fama & French, 1998; Rouwenhorst, 1999). Because the results are both mixed in developed and developing countries, more research in this field is needed, especially for developing markets. We can take advantage of studies on cross-sections of stock returns in developed markets for trading strategies both in developed and emerging markets, because in general, strategies that work well in developed markets also produce similar effects in emerging markets (van der Hart et al., 2005).

Fama and French (1993; 2015) mention that the significance of factor models can provide economic frameworks to explain tolerant risks in stock markets. In addition, portfolio constructions and factor models can be used to evaluate investment performance in long term (Fama & French, 1992; 1998). Furthermore, if portfolios constructed based on stock selections are highly correlated with common risk factors, their excess returns could be considered an additional risk (De Giorgi et al., 2019; van der Hart et al., 2005). Therefore, multifactor models are not only used for testing market efficiency and explaining stock returns, but also for evaluating the performance of an investment (Fama, 2014). In other words, testing the efficiency and effectiveness of factor models can be considered as a part of evaluation trading strategies. The intercepts of factor models, called Jensen's alphas, can be used as pricing errors and they are useful for investment evaluation (Fama, 2014; Hanauer & Lauterbach, 2019; Jagannathan & Wang, 2002).

The performance of trading strategy-based portfolio selection is measured as the return on a zero-investment portfolio, which means investors will hold a long position in winner portfolios and an offsetting short position in loser portfolios (Fama & French, 1998; Rouwenhorst, 1999; van der Hart et al., 2003). This technique is based on the arbitrage pricing theory (APT), and it has a limitation on short-selling constraints, especially in emerging markets (Alexander, 2000; Bekaert & Urias, 1996; De Roon et al., 2001). However, this approach provides useful information on which stocks should be avoided in investments (van der Hart et al., 2003). In addition, investors can use excess returns of different portfolios to evaluate the investment performance based on Jensen's alphas (van der Hart et al., 2005; 2003). Under testing the performance of portfolios, investors can understand what strategies are efficient.

2.3. Asset Pricing Theories

2.3.1. Background

Asset pricing theories are original from one simple principle: price equals expected discounted payoffs (Cochrane, 2005). In other words, an intrinsic value of an asset should equal the present value of future cash flows discounted for risk over time. However, future cash flows are not observed. These uncertainties cause difficulties for the discounting processes. Many frameworks are developed to determine relevant risk factors affecting payoffs. They can be classified as neoclassical models (Cochrane, 2005) and behavioral models (Shefrin, 2005). In contrast, Harvey et al. (2016) group hundreds of factors into common or characteristic risks.

In the neoclassical school of thought, asset pricing models are based on an assumption that investors are rational (Sharpe, 1964), and that the market is efficient (Fama, 1970). These models can be separated into absolute and relative models (Cochrane, 2005). Absolute pricing models use common risks as fundamental sources to explain asset prices, such as the general equilibrium capital asset pricing model (CAPM) developed by Sharpe (1964), and the consumption CAPM (CCAPM) developed by Breeden (1979); otherwise, in relative pricing models, an asset value is determined by understanding prices of other assets; for instance, the option pricing model developed by Black and Scholes (1973). Behavioral finance shows that investors are irrational, sentimental, and emotional (Hirshleifer & Shumway, 2003; Kahneman & Tversky, 1979; Statman et al., 2006). They are more likely to make cognitive errors when making investment decisions. Thus, this ideology focuses on the psychological phenomena of investors (Campbell et al., 2004; De Bondt, 2020; Statman et al., 2006).

According to Harvey et al. (2016), common factors are viewed as common sources of risk and they can explain the cross-section of asset returns, while characteristic factors are specific risks related to an asset. Risk exposure to a common factor is the systematic risk such as beta; otherwise, a risk not exposed to a common factor is the idiosyncratic risk, such as the standard deviation of the market model residual (Fama & MacBeth, 1973). In addition, Harvey et al. (2016) classify common risk factors in diverse groups based on the source of factors, including financial factors (Carhart, 1997; Fama & French, 1993; Sharpe, 1964), macroeconomic factors (Breeden, 1979; Lucas, 1978; Merton, 1973), microstructure factors (Amihud, 2002; Lo & Wang, 2006; Pástor & Stambaugh, 2003), behavioural factors (Baker & Wurgler, 2006; Hirshleifer & Jiang, 2010; Kumar & Lee, 2006), and accounting factors (Boudoukh et al., 2007; Chordia & Shivakumar, 2006; Da & Warachka, 2009; Hou et al., 2011). Likewise, characteristic risk factors are divided into the same groups excluding the macroeconomic category because it is common by definition (Harvey et al., 2016); for example, financial characteristics (Banz, 1981; Fama & French, 1992; Fama & MacBeth, 1973), microstructure characteristics (Barber et al., 2009; Brennan et al., 2012; Cohen et al., 2012), behavioural characteristics (Diether, et al., 2002; Fang & Peress, 2009), and accounting characteristics (Fama & French, 2006; Novy-Marx, 2013; Palazzo, 2012).

This thesis focuses on accounting and financial data, rather than using macroeconomic and behavioural data because of the objective, availability, and frequency of the information. According to Hou et al. (2015), factor models bring better performance than economic models themselves due to stock returns being available at high frequencies and fewer error measurements. Furthermore, factor models allow us to capture stock returns under the effects of state variables used in dynamic models without identifying them (Fama & French, 2015). Moreover, the research based on asset pricing theories recommends stock selection strategies for trading. This links academia and industry and is more helpful for investors in stock markets, especially for immature markets like the HSX in Vietnam.

2.3.2. The Joint Hypothesis Problem

Fama (2014) states that efficient capital markets and asset pricing models are two pillars of asset pricing. The author states that there are three forms of market efficiency, including weak form, semi-strong form, and strong form (Fama, 1970). They are different in the three relevant information subsets contained in the price formation of a stock. First, the information in the weak form is just historical prices. Second, the information in the semi-strong form includes both historical prices and other public information such as stock splits, announcements of annual earnings, announcements of mergers and acquisitions, or security issues. Third, the strong form contains all accessible information to any market participants, including monopolistic access to any information. The difficulty is how to test the efficient markets hypothesis. To do that, an asset pricing model is developed to specify the characteristics of rationally expected asset returns under the market equilibrium condition. Fama (2014) states that the test of market efficiency and tests of asset pricing models are joint tests. If the tests of asset pricing models are rejected, we do not know whether the problem is caused by an inefficient market or by a bad specification of the equilibrium model (the joint hypothesis problem) (Fama, 1970; 2014).

2.3.3. Asset Pricing Models

2.3.3.1. The Capital Asset Pricing Model (CAPM)

The CAPM is based on the single-index model and uses the mean-variance analysis developed by Markowitz (1952). He claims that “There is a rate at which investors can gain expected return by taking on variance or reduce variance by giving up an expected return." (Markowitz, 1952, p. 79). This means there is a trade-off between the expected return and risk represented by standard deviation or variance and investors are risk averse. Tobin (1958) applied the mean-variance technique to study a combination of risk-free rates through the separation theorem which says that investment choice can be divided into two steps. The first step is to determine the optimal portfolio that consists of risky assets. The second step is to allocate a budget between a riskless asset and the optimal portfolio. The CAPM states that in equilibrium, the allocation is on the capital market line (CML), with the market portfolio as the optimal portfolio (Sharpe, 1964). Accordingly, investors gain two prices: the price of time (risk-free rate) and the price of risk (the slope of the CML). However, Sharpe (1964) shows that there is a relationship between expected returns and systematic risk (market beta), but not total risk (standard deviation or variance) under diversification. In other words, unsystematic risk is uncorrelated with expected returns because it can be diversified when an asset is combined in an efficient portfolio. Furthermore, there is a positive linear relationship between market betas and expected returns, which means stocks with higher market betas should have higher returns and vice versa. In addition, in equilibrium, stocks should lie on a line called the security market line (SML).

2.3.3.2. The Arbitrage Pricing Theory (APT)

Blume and Friend (1973) show that stock returns cannot be explained by the CAPM. Consequently, the portfolio performance is biased when using the market beta. The authors criticise the unreal assumptions of the CAPM that investors are unable to borrow large amounts of money at the same risk-free rate at which they can lend. In addition, unlimited short selling that allows sellers to use proceeds from short selling to purchase other securities do not exist in stock markets. To tackle this problem, the APT proposes another framework that is an alternative to the mean-variance analysis to study the returns of assets (Ross, 1976).

The APT is based on arbitrage portfolios that use no wealth. The author shows that at equilibrium points, there are no profit opportunities for these portfolios. This means that securities having identical payoffs should have the same price. In addition, riskless investment opportunities should earn a risk-free rate. Furthermore, zero-investment or arbitrage opportunities should be eliminated under this process. There are two advantages of the APT. The first is that it holds both in equilibrium and disequilibrium situations, and the second is that it is not based on the market portfolio. Although the APT is represented in a general mathematical formula that implies the expected return of a security is a linear function of their systematic risk factors, the theory does not identify what they are.

2.3.3.3. The Intertemporal Capital Asset Pricing Model (ICAPM)

While the CAPM and APT are static, the ICAPM is a dynamic pricing model. Merton (1973, p. 867) states that "current demands are affected by the possibility of uncertain changes in future investment opportunities". This model is an extension of CAPM which considers not only a time-independent market beta, but also additional factors changing over time represented by differential equations which are called state variables. The author shows that investors should know both the investment opportunity set and the stochastic processes of the changes in the investment opportunity set. He explains that at dynamic equilibrium points, stock prices should include the demand for shares from investors and firm behaviour in supplying shares for the market. Therefore, investors should understand factors affecting these shifts such as wage income or technology. In other words, investors should determine hedge factors based on current and projected information; for example, changes in inflation, employment opportunities, or future stock market returns. However, individual investors are different in risk-averse perceptions. Thus, ICAPM is hard to generalise to a population of investors. In conclusion, ICAPM is considered a multifactor model. It attempts to determine many risks other than just market beta; however, the model does not provide concrete guidance for identifying what factors should be included.

2.3.3.4. The Consumption Capital Asset Pricing Model (CCAPM)

The CCAPM is also a dynamic model developed based on ICAPM (Breeden, 1979). Breeden (1979) argues that state variables in ICAPM are not easily identified; hence, they are not tractable for empirical studies and are not useful for decision making. The CCAPM utilises the continuous-time economic framework developed by Merton (1973); however, the model constructs a single-beta equation other than Merton’s multi-beta one. While Merton (1973) builds the utility function of individuals based on their aggregate wealth, Breeden (1979) uses consumption to study expected returns at equilibrium. The author states that the marginal utility of consumption equals the marginal utility of wealth under optimisation. In his equation, Breeden (1979) states that at equilibrium the ratio of expected excess returns on any two assets or portfolios should be identical to the ratio of their betas measured relative to aggregate consumption. Therefore, he concludes that the relevant risk of any security is consumption beta measured by the covariance of its returns and changes in aggregate consumption divided by the variance of changes in aggregate consumption. The important point of this theory is to show the relationship between low levels of aggregate consumption and highly valued state payoffs through the relation between value and marginal rates of substitution of consumption. In other words, when the value of an additional dollar payoff in a state is high, consumption is low in that state, and vice versa.

2.4. Firm Characteristics and Stock Returns

Researchers identify patterns in average stock returns. The CAPM model shows that only the market beta (CAPM beta) explains stock returns (Lintner, 1965; Mossin, 1966; Sharpe, 1964). This model indicates that higher-beta stocks have higher returns than lower-beta stocks. In contrast, the APT model shows that average stock returns can be explained by multiple factors other than market beta. For example, Fama and French (1992) found that firm size (market capitalisation) and firm value (book-to-market ratio) can explain stock returns in the US, but the market beta cannot. These authors imply that smaller-size stocks have higher returns than bigger-size stocks, while higher-value stocks have higher returns than lower-value stocks. The differences in stock returns based on firm size and firm value are called size and value effects (anomalies). Harvey (2016) found that 316 financial anomalies are discovered in finance literature. From these findings, investors often trade stocks into asset classes (portfolios) that share a common characteristic, such as small stocks or high-value stocks to expect to gain abnormal returns (higher returns required by the market). These asset classes are called styles, and fund allocation among styles is called style investing (Barberis & Shleifer, 2003). Barberis and Shleifer (2003) state that good fundamental news will create a style. Over time, that style becomes mature because it is attracted new funds, and the prices of stocks in that style will increase. Then the style is collapsed because of arbitrage or bad news. Therefore, understanding what factors determined stock returns can help investors select the right stocks for their portfolios.

2.4.1. CAPM Beta and DCC Beta

The CAPM beta is supported in early research (Blume & Friend, 1973; Fama & MacBeth, 1973). These authors found a positive correlation between CAPM beta and stock returns on the New York Stock Exchange (NYSE) from 1931 to 1967 and from 1955 to 1968. However, CAPM beta is rejected in recent studies. There are two explanations for this inefficiency of CAPM beta. The first reason is related to the biases of the method to calculate the CAPM, and the second reason is related to other anomalies that can explain stock returns.

Scholes and Williams (1977) claim that nonsynchronous trading may affect the estimation of beta when using the standard CAPM. The authors show that stocks trading either very frequently or very infrequently on average have biases of alphas and betas by using ordinary least squares (OLS). Dimson (1979) points out that using the simple CAPM for infrequently traded stocks can cause severe biases. To tackle this problem, these authors propose adding the serial lags and leads of the market portfolio's excess return other than just using the current excess return of the market portfolio. The beta measured by Scholes and Williams (1977) is estimated by adding one lag and one lead of the market portfolio's excess return, while the beta measured by Dimson (1979) is estimated by adding five lags and five leads of the market portfolio's excess returns into the CAPM model. Scholes–Williams and Dimson's betas are estimated using daily stock return data because monthly or annual return data are less likely to suffer from the issues of nonsynchronous trading. Fama and French (1992) add a one-month lag of market return in the CAPM model and create an alternative version of the market beta called the Fama–French beta. Fowler et al. (1979) propose a simpler method to deal with thin trading by using logarithmic returns.

However, the constant beta measured by the OLS is flat in explaining stock returns (Bali et al., 2017; Fama & French, 1992). Le et al. (2018) found no effect of CAPM beta on stock returns in the Vietnamese stock market. Similarly, Bali et al. (2017) found no evidence of CAPM, Scholes–Williams, Dimson, and Fama–French's betas on stock returns. To enhance the effect of market beta, Engle (2002) invented a technique called dynamic conditional correlation (DCC) based on the GARCH model to capture dynamic correlations between assets over time and create dynamic betas. Dynamic betas are positively correlated with stock returns in the research of Bali et al. (2017), Godeiro (2013), Li (2011), Milani and Ceretta (2014). In addition, GARCH models are found to tackle thin trading and the non-linearity of stock returns (Konku et al., 2018; Pece & Petria, 2015). Furthermore, the trading strategy of buying the highest DCC beta and selling the lowest DCC beta earns between 0.6 per cent and 0.8 per cent monthly.

Although the CAPM model found a positive correlation between stock returns and their beta, some studies show a negative relation (Ali & Badhani, 2021; De Giorgi et al., 2019; Frazzini & Pedersen, 2014). Frazzini and Pedersen (2014), De Giorgi et al. (2019) show that the betting against beta (BAB) strategy which buys low-beta stocks and sells high-beta stocks brings a positive return. Frazzini and Pedersen (2014) found that long low-beta stocks and short high-beta stocks produce significant positive returns in the US and 20 international equity markets. In addition, De Giorgi et al. (2019) collect data on NYSE, AMEX, and NASDAQ and the authors show that the strategy that buying the lowest-beta stocks and selling the medium-beta stocks earns a negative return, approximately −0.1 per cent monthly. However, the strategy that buying the medium-beta stocks and selling the highest-beta stocks earns a positive return, approximately 4.5 per cent abnormal return. Claessens et al. (1995) found evidence against the CAPM which shows that only nine of the beta coefficients are significant, one of which is negative in 19 emerging countries. Rouwenhorst (1999) states that no evidence that high beta stocks gain higher returns than low beta stocks in 20 emerging markets. Hanauer and Lauterbach (2019) also found a negative correlation between beta and stock returns in emerging markets. Recently, Ali and Badhani (2021) also found that low-beta stocks have higher returns than high-beta stocks in the Indian market. Table 2.1 below shows the summary of empirical studies on market beta and stock returns.

Table 2.1: Empirical Studies of Market Beta

Author(s)	**Sample**	**Beta Estimation**	**Findings**
Fama & French (1992)	Nonfinancial firms in the CRSP and COMPUSTAT databases in the US, from 1962 to 1989.	OLS.	Beta cannot explain stock returns; however, the size (market capitalisation) and the value (book-to-market equity) can be.

Author(s)	Sample	Beta Estimation	Findings
Li (2011)	1,426 stocks traded in G7, from 1980 to 2007.	OLS, Multivariate GARCH (CCC and DCC), and Markov regime-switching (MRS).	The dynamic betas estimated by GARCH and MRS models have better performance than the constant beta estimated by the OLS.
Godeiro (2013)	28 stocks in the Ibovespa portfolio, Brazil, from 1995 to 2012.	Multivariate GARCH (DCC) and Kalman Filter.	Beta measured by the DCC-GARCH has more power than the beta measured by the Kalman Filter.
Frazzini & Pedersen (2014)	55,600 stocks in the US and 20 international markets, from 1926 to 2012.	OLS.	Asset returns and beta are negatively correlated. Buying low-beta stocks and selling high-beta stocks produce positive returns.
Bali et al. (2017)	Nondelisting stocks in the CRSP and COMPUSTAT databases in the US, from 1963 to 2013.	OLS, Multivariate GARCH (DCC).	The dynamic conditional beta measured by the GARCH model has a better performance in explaining stock returns than betas measured by OLS (with or without adjustment for thin trading).
Le et al. (2018)	703 listed stocks in the HSX and HNX, Vietnam, from 2007 to 2012.	OLS.	Stock returns and beta are positively correlated. In particular, beta is more significant in explaining stock returns with the presence of firm size (market capitalisation).
De Giorgi et al. (2019)	Stocks in the CRSP and COMPUSTAT databases in the US, from 1927 to 2016.	OLS.	There exists a concave correlation between stock returns and market beta. In addition, buying medium-beta and selling high-beta stocks earn higher alpha than buying low-beta and selling high-beta stocks.
Ali & Badhani (2021)	650 stocks traded on the NSE and BES exchanges in India, from 2002 to 2018.	OLS.	The correlation between market beta and stock return is nonlinear. Returns of high-beta stocks are lower than those of low-beta stocks. The strategy of buying medium-beta and selling high-beta stocks earns the highest return.

This thesis tests if higher-beta stocks have higher returns than lower-beta stocks in the HSX. Therefore, the hypothesis based on betas is as follows:

> HA1: stock returns and market beta (static and dynamic) on the HSX are positively correlated.

The positive sign of HA1 has been based on the CAPM model developed by Sharpe (1964), and the new development of dynamic beta by Engle (2002). Based on this hypothesis, this thesis forms trading strategies with the assumption that buying stocks that have higher beta have higher returns than buying lower stocks that have lower beta. Therefore, the arbitrage strategies that buy stocks that have a higher beta and sell stocks that have a lower beta should have positive returns.

2.4.2. Firm Size

We may observe that large stocks have lower returns than small stocks. This is a size anomaly or size effect in finance. Banz (1981) examined the relationship between the market value of common stocks with their returns. The sample test for stocks listed on the NYSE between 1926 and 1975 shows that the returns of firms with larger market capitalisation were lower than those with smaller market value. Fama and French (1992) show that market beta does not describe the cross-sectional stock returns; however, the firm size (computed by the logarithm of ME) has a negative relationship with stock return. In detail, although smaller stocks have higher average returns from 1963 to 1990 on the NYSE (New York Stock Exchange), AMEX (American Stock Exchange), and NASDAQ (National Association of Securities Dealers Automated Quotations System), the market beta does not explain the average stock returns for the same period. Similarly, while Rouwenhorst (1999) also found that small stocks have higher returns than big stocks in 20 emerging markets, the author rejects the explanation of market beta to stock returns. The strong effect of firm size is found in emerging markets (Hilliard & Zhang, 2015; Leite et al., 2018; Pandey & Sehgal, 2016; Vasishth et al., 2021). Dang et al. (2017) found that firm size is negatively correlated with stock returns on HSX and HNX from 2012 to 2016. Likewise, Le et al. (2018) point out a negative correlation between stock returns and firm size using listed stocks in two exchanges in Vietnam between 2007 and 2012.

There are some explanations for the effect of firm size on stock returns. Banz (1981) claims that the higher returns of small stocks compared to large stocks may be caused by their higher information risk due to the lower quality of information of these firms. He explains that because of insufficient information about small firms, investors will not desire to buy small stocks and they will require higher returns for those stocks. Chan and Chen (1991), Vassalou and Xing (2004), Hwang et al. (2010) explain that small firms have not been doing well and have higher financial distress compared to large firms. Because small firms are expected to bear higher financial distress risks, investors require higher returns for these stocks. In addition, Amihud (2002) found that illiquidity is stronger for small stocks than for large stocks. The author suggests that the effect of firm size is a proxy for illiquidity. He explains that in times of dire liquidity, small stocks are more unattractive than large stocks because of illiquidity risk. Therefore, they are priced at a higher risk premium than large stocks.

In contrast, Nurhayati et al. (2021) found that firm size and stock returns are positively correlated in the Indonesian market. These authors found that large firms obtain higher profits. Therefore, these stocks attract more investors and are easier to access the market than small firms. Similarly, Claessens et al. (1995) found evidence of positive returns when investing in large companies in emerging markets. They explain that these markets are opened to foreign investors who are first attracted by big companies. Therefore, this may increase the returns of blue-chip stocks compared to penny-chip stocks. Furthermore, big companies in these countries are easier to access cheaper capital than small companies through subsidies from their government or by lower-cost financing. Hence, investors prefer to invest in large stocks.

However, Hou et al. (2011) reject the effect of firm size on global stock returns in 49 countries from 1981 to 2003. In addition, Cakici et al. (2016) also found that size fails to explain stock returns in 18 emerging stock markets from 1990 to 2013. Horowitz et al. (2000) show that the effect of firm size is not detected in the US market from 1980 to 1996. The authors conclude that this effect is an academic discovery. It is strong in-sample evidence, but weak out-of-sample results. Batten and Vo (2014) found no effect of firm size on the HSX from 2007 to 2010. Likewise, van der Hart et al. (2003), the strategy based on firm size is insignificant in 32 emerging markets. Chin and Nguyen (2015) used a similar methodology developed by Hart et al. (2003) and also found that investing based on firm size is insignificant in the HSX between 2006 and 2014. Alquist et al. (2018) found that the effect of firm size reduced quickly after its publication. These authors found that the size effect is weaker than other anomalies such as value and momentum. Similarly, Barry et al. (2002) also found that the effect of firm size is weaker than the effect of firm value in 35 emerging markets. Dimson et al. (2017) found that the effect of firm size disappeared and reappeared over several long periods. This effect also appeared in Indonesia, Gulf Cooperation Council (GCC) market, and India (Alhashel, 2021; Hendrawaty & Huzaimah, 2019; Vasishth et al., 2021). Table 2.2 below shows the summary of empirical studies on firm size and stock returns.

Table 2.2: Empirical Studies of Firm Size

Author(s)	Sample	Size Estimation	Findings
Fama & French (1992)	Nonfinancial firms, collected from the CRSP and COMPUSTAT	Natural logarithm of market capitalisation.	Firm size is negatively correlated with portfolio returns. Furthermore, small-size portfolios have

Author(s)	Sample	Size Estimation	Findings
	databases in the US, from 1962 to 1989.		higher beta than big-size portfolios.
Claessens et al. (1995)	19 emerging stock markets, collected from the emerging markets database, maintained by IFC, from 1986 to 1993.	Relative market capitalisation (a firm's market capitalisation is divided by total market capitalisation).	Stock returns and firm size are positively correlated. Because large firms in emerging countries can access cheaper capital through subsidies from their government or lower-cost international financing, large stocks are preferred over small stocks in this period.
Cakici et al. (2016)	18 emerging stock markets, collected from the Datastream database, between 1990 and 2013.	Market capitalisation (measured in millions of dollars).	In Asia, size premium is statistically significant only in China. In Latin America and Europe, the size premium is not significant. In particular, buying small-size and selling big-size stocks produce negative returns in Hungary.
Dang et al. (2017)	274 listed companies on the HSX and HNX, Vietnam, from 2012 to 2016.	Natural logarithm of total assets.	Firm size is negatively correlated with stock returns.
Dimson et al. (2017)	US and UK stocks, collected from the CRSP and NSCI databases, between 1926 and 2016.	Market capitalisation.	In the US, annual returns of small-cap and micro-cap stocks (12.1% and 12.7%, respectively) are higher than returns of large-cap stocks (9.7%). A similar pattern is found in the UK. Investing in micro-cap stocks earns 17.9% annually, while investing in large-cap stocks earns 12% annually.
Alquist et al. (2018)	24 equity markets, collected from World Scope, between 1984 and 2017.	Market capitalisation.	The CAPM alphas of the size factor (SMB) are negative in 13 of 24 markets. However, all t-statistics are insignificant. The CAPM alphas of the SMB factor are positive and higher than they are in the US; however, they are also insignificant.
Hendrawaty & Huzaimah (2019)	45 listed companies on the Indonesian stock exchange, from 1997 to 2017.	Natural log market capitalisation.	Firm size and stock returns are negatively correlated. Therefore, small stocks have higher returns than big stocks.

Author(s)	Sample	Size Estimation	Findings
Nurhayati et al. (2021)	17 listed companies on the Indonesian stock exchange, from 2014 to 2018.	Total assets.	Firm size and stock returns are positively correlated because large firms produce higher profits; therefore, they attract investors to invest.
Alhashel (2021)	GCC markets, collected from the Compustat Global database, between 2001 and 2016.	Market capitalisation.	Portfolio returns and firm size are negatively correlated.
Vasishth et al. (2021)	200 stocks from NIFTY 200 index, India, from 2005 to 2018.	Market capitalisation.	The size effect is significant for both measurements using market capitalisation and total assets. In addition, different sorting methods using quintiles and deciles of portfolios do not affect the significance of the size effect.

This thesis tests if smaller-size stocks have higher returns than bigger-size stocks in the HSX. Therefore, the hypothesis based on firm size is as follows:

HA2: stock returns and firm size on the HSX are negatively correlated.

The negative sign of HA2 has been based on the arguments that the higher information risk of small-size firms due to the lower quality of information (Banz, 1981), or higher financial distress (Chan & Chen, 1991; Hwang et al., 2010; Vassalou & Xing, 2004), or higher illiquidity (Amihud, 2002). Based on this hypothesis, this thesis forms trading strategies with the assumption that buying smaller-size stocks have higher returns than buying bigger-size stocks. Therefore, the arbitrage strategies that buy smaller-size stocks and sell bigger-size stocks will have positive returns.

2.4.3. Firm Value

Many studies show that value stocks generate higher long-term returns than growing stocks (Basu, 1977; Bhandari, 1988; Chan et al., 1995; Fama & French, 1992; Jaffe et al., 1989; Lakonishok et al., 1994; Rosenberg et al., 1985). In other words, stock returns have a positive relationship with their firm values. Different variables are proxies for a value stock, including low prices relative to their earnings per share (EPS) (Basu, 1977; Jaffe et al., 1989), low price compared to its dividend (Lakonishok et al., 1994), high ratio of debt to equity (Bhandari, 1988), the low prices-to-the book value of equity (Rosenberg et al., 1985), and high book-to-market equity (Chan et al., 1995; Fama & French, 1992; Lakonishok et al., 1994). Fama and French (1992) show that the relations between these variables and stock returns are explained by two variables: market capitalisation and the book-to-market ratio. The authors show that the book-to-market ratio may capture the relative distress effect developed by Chan et al. (1991). They explain that the prospects of firms with high book-to-market ratios are poorer than those with low book-to-market ratios. Therefore, stocks with high book-to-market ratio have lower prices than stocks with low book-to-market ratio. In other words, stocks with high book-to-market ratio require the higher returns than stocks with low book-to-market ratio because they bear higher risk (Fama & French, 1992; 1995). In addition, Fama and French (1993) develop a risk model including market capitalisation and book-to-market ratio to explain for size and value effect, respectively. Lakonishok et al. (1994) give another reason based on overreaction. These authors explain that naïve investors tend to overbuy glamour stocks (low book-to-market ratio) that have performed well in the past, so that these stocks become overpriced. However, they oversell value stocks (high book-to-market ratio) have performed badly, so that these stocks become underpriced. They state that a low book-to-market ratio may be signal of a company with attractive growth prospects that are not shown in the book value, but are shown in the high market prices. They conclude that a stock with low risk and their future cash flows are discounted at that low rate would have a low book-to-market ratio.

Blackburn and Cakici (2017) found that although the book-to-market ratio is different across the four regions including North America, Europe, Japan, and Asia, this variable and stock returns are significantly positively correlated. The book-to-market ratio in Japan and Asia is higher than in North America and Europe. In addition, Hanauer and Linhart (2015) show a strongly positive and highly significant book-to-market ratio on stock returns in four emerging market regions: Latin America, EMEA, ASIA, and BRIC. Furthermore, Hanauer and Lauterbach (2019) found that the book-to-market ratio is positively correlated with stock returns in 28 emerging markets between 1995 and 2016. Cordis (2014) found that the logarithm of book-to-market ratio and stock returns are positively correlated in the US market. Bali et al. (2016) also found that the distribution of book-to-market ratio is highly positively skewed. To reduce the effect of extreme values in statistical analysis, these authors recommend taking the logarithm of this variable.

According to van der Hart et al. (2003), stock selections based on value (book-to-market ratio) generate positive excess returns in 32 emerging countries from 1985 to 1999. In addition, van der Hart et al. (2005) found the strategy of buying high-value stocks and selling low-value stocks generates positive returns in emerging markets using stocks included in the IFC Investable Composite Index between 1998 and 2004. Chin and Nguyen (2015) found that higher-value stocks (low earning-to-price ratio) have higher returns on the HSX between 2006 and 2014. The authors found that the highest returns come from the three-month and six-month buying stocks with the highest earning-to-price (E/P) ratio and selling stocks with the lowest E/P at 2.47 per cent and 2.07 per cent, respectively. Hanauer and Lauterbach (2019) also found that portfolios with higher firm value (higher book-to-market ratio) have higher returns in 28 emerging markets from 1995 to 2016. While Utomo and Tjandra (2015) found that returns of value stocks are significantly higher than growth stocks in Indonesia, Hu et al. (2019) found that the effect of value stocks exists in China, but it is not strong. In contrast, Maiti and Balakrishnan (2020) found that value stocks have lower returns than growth stocks in India. Alhashel (2021) found that this effect exists in GCC markets, except for the reversed pattern in Kuwait and Saudi Arabia. Table 2.3 below shows the summary of empirical studies on value and stock returns.

Table 2.3: Empirical Studies of Firm Value

Author(s)	Sample	Value Estimation	Findings
Fama & French (1992)	Nonfinancial firms, collected from the CRSP and COMPUSTAT databases in the US, from 1962 to 1989.	The natural logarithm of the book-to-market equity ratio (BTM).	Firm value is positively correlated with portfolio returns. A high ratio of BTM shows that the prospects of those firms are poorer than firms with low BTM.
Batten &Vo (2014)	All listed firms on the HSX, from 2007 to 2010.	Book-to-market equity ratio (BTM).	Stock returns are positively correlated with BTM. The fixed-effect model is preferred to the random-effect model.
Utomo & Tjandra (2015)	594 listed stocks in the Indonesian stock exchange, collected from Bloomberg Terminal, Datastream, and S&P Capital IQ, between 1994 and 2014.	Earnings yield (E/P), book-to-market equity ratio (BTM), cash flow yield (C/P), and dividend yield (D/Y).	Returns of value portfolios measured by different measurements are higher than returns of growth portfolios. Furthermore, cumulative returns, risk-adjustment returns using CAPM, and Fama–French three-factor models of all value portfolios are higher than the aggregate mutual fund industry (Indonesian Mutual Funds).
Hanauer & Linhart (2015)	21,612 stocks in 21 emerging markets and 63,775 stocks in 24 developed markets, collected from Datastream and Worldscope, between 1996 and 2012.	Book-to-market equity ratio (BTM).	The firm value factor in emerging markets is nearly double compared to that in developed markets. In particular, the value factor shows the strongest effect in the BRIC region.
Blackburn & Cakici (2017)	23 developed markets from North America (5,288 firms), Europe (5,129 firms), Japan (3,129 firms), and Asia (2,186 firms), from 1993 to 2014.	Book-to-market equity ratio (BTM).	Although the BE/ME is different across the four regions, the average values of this coefficient are all positive in Fama–MacBeth regressions for three cases: all stocks, small stocks, and big stocks. While Japan shows that this relation is significant for all cases, this relation is insignificant for big stocks in North America, Europe, and Asia.

Author(s)	Sample	Value Estimation	Findings
Hanauer & Lauterbach (2019)	6,535 firms in 28 emerging markets, collected from Datastream and Worldscope databases, between 1995 and 2016.	Book-to-market equity ratio (BTM), earning to price (E/P), cash flow to price (CF/P).	There exists a monotonic relationship from the bottom to the top quintile portfolio when stocks are sorted by BTM, E/P, CF/P. The higher-value portfolios have higher returns than lower-value portfolios. The Fama–MacBeth regression shows that stock returns are positively correlated with these variables.
Hu et al. (2019)	311 listed companies in the Chinese stock market, collected from the Chinese Capital Market (CCM) database, between 1995 to 2016.	Book-to-market equity ratio (BTM).	When portfolios are sorted by BTM, portfolios having higher this ratio have higher returns. Although the long-short portfolio between the top and the bottom portfolios produces a positive return, it is statistically insignificant. Therefore, the value effect is not robust in this market.
Maiti & Balakrishnan (2020)	371 nonfinancial companies of BSE 500 index, Indian stock market, collected from Bloomberg database, between 2003 to 2016.	Price-to-book value ratio (P/B).	Portfolios with higher P/B have lower returns than portfolios with lower P/B. Therefore, the return of value factor is the return of the low-P/B portfolios minus the return of the high-P/B portfolios. This is the reversed pattern of value effect.
Alhashel (2021)	GCC markets, collected from the Compustat Global database, between 2001 and 2016.	Book-to-market equity ratio (BTM), earning to price (E/P).	Stocks sorted by the BTM show that higher BTM portfolios have significantly higher returns than lower BTM portfolios. However, the sorting using E/P shows insignificance. In particular, higher-E/P portfolios have lower returns in Kuwait and Saudi Arabia.

This thesis tests if higher-value stocks have higher returns than lower-value stocks in the HSX. Therefore, the hypothesis based on firm value is as follows:

HA3: stock returns and firm value on the HSX are positively correlated.

The positive sign of HA3 has been based on the arguments that high-value stocks imply higher risk (Fama & French, 1995), or these stocks are underpriced by overselling (Lakonishok et al., 1994). Based on this hypothesis, this thesis forms trading strategies with the assumption that buying higher-value stocks have higher returns than buying lower-value stocks. Therefore, the arbitrage strategies that buy higher-value stocks and sell lower-value stocks will have positive returns.

2.4.4. Momentum

Jegadeesh and Titman (1993) show that stocks performing well in the past from three to 12 months are predicted to outperform in the future in the US market from 1965 to 1989. In other words, investors who buy stocks with high returns over the previous three months to one year (the winners) and sell stocks with low returns over the same period (the losers) can achieve abnormal returns. This effect is called momentum (the returns of stocks during previous months) which is considered the persistent expected stock returns. Chui et al. (2010) found that buying the winners and selling the losers (based on six-month momentum calculated by the past six-month cumulative returns) bring positive returns for investors in international markets except for Japan, Korea, Taiwan, and Turkey between 1980 and 2003. In addition, Rouwenhorst (1999) also found that the momentum effect calculated from prior six-month returns is significant in 20 emerging markets except for Argentina, Indonesia, and Taiwan. The author states that the average momentum returns in emerging stock markets are lower than those that have been found in developed markets. Fama and French (2012) show that the momentum effect is found everywhere in 23 countries in North America, Europe, and the Asia Pacific. Van der Hart et al. (2003) found that the momentum effect exists in 32 emerging markets from 1985 to 1999. However, Cakici et al. (2016) rejected the momentum effect in 18 emerging markets from 1990 to 2013.

Teplova and Mikova (2015) state that the momentum effect challenges the weak form of the efficient market hypothesis. While proponents of the rational approach explain that abnormal momentum returns are coming from higher risk, opponents claim that the momentum effect can be explained by irrational behaviour (Singh & Walia, 2022; Subrahmanyam, 2018). Rational investors believe that profit from momentum investing is the reward for bearing high risk. This approach considered momentum as systematic risk and is explained by risk-based models (Johnson, 2002; Li, 2018; Ruenzi & Weigert, 2018). In contrast, behaviourists are sceptical about data snooping on rational models, and they claim that momentum should be explained by behavioural finance (Docherty & Hurst, 2018; Grinblatt & Han, 2005; Hong et al., 2000; Hur & Singh, 2019). Fama and French (1996) test the momentum effect by the three-factor model and they found that size and value factors cannot explain the momentum. The authors found that the intercepts of the models are strongly negative for the losers (low past returns) and strongly positive for the winners (high past returns). In addition, the authors state that losers behaved more like small and distressed stocks, while winners were similar to large stocks with low financial distress. Chan et al. (1996) also found that size and value factors in the three-factor model cannot explain the momentum effect. These authors explain that because investors slowly discount new information, a stock with low (high) past returns will continue low (high) subsequent returns.

Rouwenhorst (1999) found that the momentum strategy is efficient in 17 emerging countries from 1982 to 1997; however, the average returns of this strategy are lower than those in developed countries. In addition, profits based on momentum are found significant in Asian stock markets excluding Japan (Chui et al., 2010; Iihara et al., 2004; Liu & Lee, 2001). The efficiency of the momentum strategy is also found in Asia and Africa (Griffin et al., 2003). Evidence of profits from momentum is also found in India and Bangladesh (Ansari & Khan, 2012; Khan & Rabbani, 2017; Sehgal & Balakrishnan, 2008). Van der Hart et al. (2005; 2003) show that the momentum strategy in emerging markets is consistent with findings in developed markets. Chin and Nguyen (2015) also found a positive relationship between momentum and stock returns on the HSX from 2006 to 2014. Similarly, this momentum effect was found significant in Tunisia, India, and the US (Boussaidi & Dridi, 2020; Singh & Walia, 2021; Wang et al., 2021). Rashid et al. (2019) found that while higher-momentum stocks have higher returns than lower-momentum stocks for the group of big firms, the reverse pattern was found for the group of small firms in Pakistan. Table 2.4 below shows the summary of empirical studies on momentum and stock returns.

Table 2.4: Empirical Studies of Momentum Effects

Author(s)	Sample	Momentum Estimation	Findings
Fama & French (2012)	23 international markets in North America, Europe, Japan, and the Asia Pacific, from 1989 to 2011.	Cumulative returns of the past 11 months.	The portfolios formed by size and momentum show that higher-momentum portfolios (winners) have higher returns than lower-momentum portfolios (losers) in all markets except Japan.
Hanauer & Linhart (2015)	21,612 stocks in 21 emerging markets and 63,775 stocks in 24 developed markets, collected from Datastream and Worldscope, between 1996 and 2012.	Cumulative returns of the past 11 months.	The momentum factor is positive for all samples. Furthermore, while the three-factor model developed by Fama & French (1993) cannot explain the returns of size-momentum portfolios, adding the momentum factor explains the risk of those portfolios.
Chin & Nguyen (2015)	299 listed stocks on two stock exchanges HSX and HNX in Vietnam, from 2006 to 2014.	Past one-month returns.	The top-momentum portfolios have higher returns than the bottom-momentum portfolios for different holding periods (1, 3, 6, 9, 12, and 24 months). The highest average return is recorded

Author(s)	Sample	Momentum Estimation	Findings
			for one-month holding. Longer holding periods reduce the momentum effect.
Hanauer & Lauterbach (2019)	6,535 firms in 28 emerging markets, collected from Datastream and Worldscope databases, between 1995 and 2016.	Cumulative returns of the past 11 months.	Momentum is significant in both portfolio sorts and cross-sectional regression. This shows that the momentum effect is strong in emerging markets.
Rashid et al. (2019)	Nonfinancial firms in the Pakistan stock market, from 2000 to 2013.	Cumulative returns of the past 11 months.	While higher-momentum portfolios have higher returns than lower-momentum portfolios for big stocks, there is an inverse pattern for small stocks. The momentum factor is positive and significant.
Boussaidi & Dridi (2020)	904 nonfinancial firms traded on the Tunis stock exchange, from 1999 to 2016.	Cumulative returns of the past 3, 6, 9, and 12 months.	The strategies that buy the winner portfolio (high momentum) and sell the loser portfolio generate significant and positive returns, especially for momentum calculated by the cumulative returns of six and nine months. In addition, the five-factor model developed by Fama & French (2015) fails to explain momentum profits.
Singh & Walia (2021)	458 listing stocks on Bombay stock exchange, India, collected from Prowess database, from 2002 to 2019	Cumulative returns of the past 11 months.	Raw returns of momentum strategies produce positive and significant returns for different holding periods (1, 3, 6, 9, and 12 months). In addition, the risk-adjusted returns by the CAPM model (Sharpe, 1964) and the three-factor model (Fama & French, 1993) cannot explain the momentum profit for a short holding period from one to six months.
Wang et al. (2021)	Nonfinancial stocks on NYSE, collected from CRSP, COMPUSTAT, and I/B/E/S databases, in the period 1963–2019.	Cumulative returns of the past 52 weeks.	The momentum effect is short-lived. Momentum profits from long-short strategies are significant within one year (52 weeks). The momentum profits are indifferent from

Author(s)	Sample	Momentum Estimation	Findings
			zero from week 52 to week 104. These profits cannot be explained by the CAPM model (Sharpe, 1964), the three-factor model (Fama & French, 1993), and the four-factor model (Carhart, 1997).

This thesis tests if higher-momentum stocks have higher returns than lower-momentum stocks in the HSX. Therefore, the hypothesis based on momentum is as follows:

HA4: stock returns and momentum are positively correlated on the HSX.

The positive sign of HA4 has been based on the arguments that higher returns of high momentum stocks are from higher risk, or irrational behaviour (Carhart, 1997; Jegadeesh & Titman, 1993; Singh & Walia, 2020; Subrahmanyam, 2018). Based on this hypothesis, this thesis forms trading strategies with the assumption that buying higher-momentum stocks have higher returns than buying lower-momentum stocks. Therefore, the arbitrage strategies that buy higher-momentum stocks and sell lower-momentum stocks will have positive returns.

2.4.5. Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR)

Ang et al. (2006) state that investors pay more attention to downside losses than upside gains. They explain that the price of a stock tends to decrease when a market declines more than it increases when the market rises. They measured downside risk by using betas when the market declines (return is below its mean). They also found that stocks with high past downside risk predict high returns in the future. VaR is another proxy of a security risk that quantifies the downside risk (the maximum loss at a given confidence level over a period of time). Jorion (1996) states that VaR can predict the worst loss over a horizon with a given confidence level; therefore, this measurement is powerful in explaining stock returns. VaR is used in many financial institutions such as banks, insurance companies, investment firms, and credit rating agencies. However, VaR is not well researched in empirical studies (Aziz & Ansari, 2017). Bali and Cakici (2004) conducted the first research on the relation between stock returns and Value-at-Risk, and they show that VaR has a positive relationship with stock returns on both stock and portfolio levels in the US stock market from 1958 to 2001. Bali et al. (2009) found that VaR and portfolio returns are positively correlated in the US stock market between 1926 and 2005. Furthermore, Bali et al. (2007) found a positive correlation between VaR and expected returns on live funds in the period 1995–2003. The authors state that higher VaR portfolios earn higher annual returns at 9 per cent. However, Trimech and Benammou (2012) show a negative correlation between portfolio returns and VaR in the French market. In emerging countries, VaR is supported by Aziz and Ansari (2017), Chen et al. (2014), and Iqbal and Azher (2014). To the best of my knowledge, there is no article published in Vietnam in this field.

VaR can contribute to explaining the stock returns because safety-first investors are risk-averse. They will select a portfolio that minimises a downside risk that is a function of VaR (Bali et al., 2009; Baumol, 1963; Levy & Sarnat, 1972; Roy, 1952). In addition, because financial institutions and nonfinancial firms hold risky portfolios including stocks, bonds, currencies, and derivatives, they need to measure the potential losses. Furthermore, credit rating and regulatory agencies need to evaluate the likely losses on portfolios to set capital requirements and issue credit ratings. These organisations can use VaR to compute the probability and magnitude of potential losses on their portfolios (Bali et al., 2009). Bali et al. (2009) and Carr et al. (2002) suggest that extreme movements in stock returns can be considered risk factors that may have the power in explaining stock returns. Therefore, VaR measures the extreme values from the left tail can be considered as a source of risk of stock returns. In addition, the stock returns are not normally distributed. Therefore, extreme values arise more frequently than predicted by the normal distribution. Hence, VaR is a superior measure of risk compared to the traditional risk measures using variance and standard deviation (Bali et al., 2007). Harvey and Siddique (2000) show that risk-averse investors desire positively skewed assets more than negatively skewed assets. In other words, these investors prefer right-skewed stock returns to left-skewed stock returns. Therefore, left-skewed assets are less desirable, and investors require higher returns to buy them. Dittmar (2002) shows that risk-averse investors prefer low-kurtosis stock returns to high-kurtosis stock returns. Because low-kurtosis assets have a lower probability mass in the tails than high-kurtosis assets, the extreme values of low-kurtosis assets occur less frequently than the extreme values of high-kurtosis assets. Therefore, low-kurtosis assets are less risky than high-kurtosis assets. Hence, high-kurtosis assets are less desirable, and investors require higher returns to buy them.

Bali et al. (2007) state that VaR becomes larger when stock returns are negative skewness and thicker tails. Therefore, the skewness and kurtosis of asset returns may specify a positive correlation between stock returns and VaR. Although VaR is the most used to measure risk in commercial banks and financial institutions (Abad et al., 2014; Tian et al., 2019; Unbreen & Sohail, 2020), however, it does not consider fat tail risks (Artzner et al., 1999; Luciano & Marena, 2002). To improve the measurement of VaR, the studies by Artzner et al. (1999) and Uryasev (2000) propose to use the CVaR to measure the tail risks. Furthermore, portfolios constructed using mean-CVaR analysis have higher performance than using mean-variance analysis (Unbreen & Sohail, 2020).

Aziz and Ansari (2017) found that the monthly hedge portfolio return based on VaR gains 1.56 per cent and the CAPM alpha is 1.03 in the Indian stock market between 1999 and

2004. Both are statistically significant for the equal-weighted portfolios. However, value-weighted portfolios are not significant. Bali and Cakici (2004) found that the monthly average returns of difference VaR portfolios is approximately 0.96 per cent using non-financial stocks listed on the NYSE, AMEX, and NASDAQ from 1958 to 2001. Bali et al. (2007) studied hedge fund returns using data from Tremont TASS and Hedge Fund Research Incorporation in the period 1995–2003, and show that VaR and average returns are negatively correlated for defunct funds; however, for live funds this relation is positive. In particular, a hedge portfolio (buying live funds and selling defunct funds) brings an annual return from 8 per cent to 10 per cent. Both VaR and CVaR are similar because they measure tail risks; therefore, CVaR and stock return are expected to be positively correlated. In contrast, the CVaR is negatively correlated with stock returns in China, Europe, and Vietnam markets (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019). Table 2.5 below shows the summary of empirical studies on Value-at-Risk (VaR) and stock returns.

Table 2.5: Empirical Studies of VaR (CVaR)

Author(s)	Sample	VaR Estimation	Findings
Bali & Cakici (2004)	All nonfinancial stocks on the NYSE, AMEX, and NASDAQ, from 1958 to 2001.	Non-parametric VaR (1%, 5%, 10% VaR).	Portfolios containing higher-VaR stocks have higher returns. Furthermore, Fama–MacBeth regressions show that stock returns and VaR are positively correlated.
Bali et al. (2007)	843 hedge funds from two databases TASS and HFR, from 1995 to 2003.	Non-parametric method (5% VaR) and parametric method (1% VaR).	For live funds, higher-VaR portfolios have higher returns. However, for defunct funds, higher-VaR portfolios have lower returns.
Tokpavi & Vaucher (2012)	Stocks in the STOXX® Europe 600, from 1998 to 2011.	Non-parametric method and semi-parametric method (10% CVaR).	Lower-CVaR portfolios have higher returns than higher-CVaR portfolios for CVaR calculated by non-parametric and semi-parametric methods. CVaR is highly correlated with volatility (standard deviation). Controlling for volatility, the profits

Author(s)	Sample	VaR Estimation	Findings
			earned by buying the bottom quintile CVaR portfolio and selling the top quintile CVaR portfolio reduce significantly.
Iqbal & Azher (2014)	231 listed stocks on the Karachi stock exchange (KSE), Pakistan, from 1992 to 2008.	Non-parametric method (1%, 5%, 10% VaR).	Higher-VaR portfolios have higher returns than lower-VaR portfolios. In addition, VaR can be considered a risk factor to explain stock returns.
Aziz & Ansari (2017)	Stocks in BSE-500 Index, India, collected from Prowess database, from 2001 to 2014.	Non-parametric method (1%, 5%, 10% VaR).	Fama–MacBeth regressions show that VaR and stock returns are positively correlated at different loss probabilities (1%, 5%, and 10%. Higher-VaR portfolios have higher returns than lower-VaR portfolios.
Vo et al. (2019)	10 industry indexes in ASEAN countries, from 2007 to 2016.	Non-parametric method (5% CVaR).	In Vietnam, the healthcare industry has the lowest CVaR, but produces the highest return. In Thailand, the basic material industry has the highest CVaR; however, it has the lowest returns.
Ling & Cao (2020)	A-shares firms listed on the Shanghai and Shenzhen stock exchanges, collected from Wind and CSMAR databases, from 1995 to 2016.	Non-parametric method (1%, 5%, 10% CVaR).	Higher-CVaR portfolios have lower returns than lower-CVaR portfolios. Fama–MacBeth regressions show that stock returns are negatively correlated with CVaR.
Unbreen & Sohail (2020)	Listed stocks on the Pakistan stock exchange, from 2009 to 2018.	Non-parametric method (5% CVaR).	Portfolios constructed using mean-CVaR analysis have higher performance than portfolios constructed using mean–variance analysis.

This thesis tests if higher-VaR stocks have higher returns than lower-VaR stocks and if higher-CVaR stocks have lower returns than lower-CVaR stocks in the HSX. Therefore, the hypothesis based on VaR and CVaR are as follows:

HA5: stock returns on the HSX have a positive relationship with VaR.

HA6: stock returns on the HSX have a negative relationship with CVaR.

The positive sign of HA5 has been based on the arguments that higher loss means higher risk and these stocks should be rewarded by higher returns (Bali & Cakici, 2004; Bali et al., 2007). In contrast, the negative sign of HA6 has been based on the arguments of herd behaviour or the limitation of short selling (Baker & Wurgler, 2006; Ling & Cao, 2020; Tokpavi & Vaucher, 2012).

Based on these hypotheses, this thesis forms trading strategies with the assumption that buying higher-VaR stocks has higher returns than buying lower-VaR stocks. Therefore, the arbitrage strategies that buy higher-VaR stocks and sell lower-VaR stocks will have positive returns. In contrast, buying lower-CVaR stocks has higher returns than buying higher-CVaR stocks. Therefore, the arbitrage strategies that buy lower-CVaR stocks and sell higher-CVaR stocks will have positive returns.

2.4.6. Illiquidity

Lesmond et al. (1999) state that with higher transaction costs, stocks will have less frequent price movements and more zero returns than stocks having low transaction costs. These authors propose the zero return of a stock calculated as the number of zero-return days divided by the number of trading days at a given time is the proxy of illiquidity. Therefore, this approach requires the time series of daily returns to estimate the illiquidity. The limitation of this approach is that it can lead to the same level of illiquidity for stocks in multiple periods (Chen & Sherif, 2016). Amihud (2002) shows that illiquidity premiums can explain cross-sections of stock returns in the US stock market between 1964 and 1997. Illiquidity is the daily ratio of absolute stock return divided by its dollar volume and averaged over some period. It can be considered as the daily price response related to one dollar of trading volume or it can be measured by the bid-ask spread. The former method is easily obtained by daily transactions; however, the latter requires microstructure data that are not available in many stock markets (Amihud, 2002), and the bid and ask quotes remain only for a limited time (Chen & Sherif, 2016). Martínez et al. (2005) found that illiquidity and stock returns are negatively correlated in the Spanish stock market from 1991 to 2000. Batten and Vo (2014) show that illiquidity does not affect stock returns in the HSX from 2007 to 2010 in stock levels. According to the authors, this discrepancy may originate from the low connection of this market to global markets. Tran et al. (2013) found a negative correlation between stock returns and liquidity in the Vietnamese stock market from 2007 to 2011.

In addition, this factor and excess return are positive correlations. Pástor and Stambaugh (2003) studied the correlation between expected stock returns and aggregate liquidity, which is portfolio-level liquidity. These authors define liquidity as the ability to trade a large number of securities quickly, at low cost, and without affecting the price. The research shows that in the US stock market between 1966 and 1999, stocks with high liquid risk gained higher returns compared to stocks with low liquid risk (approximately 7.5% annually) after adjusting for the market risk, size, value, and momentum factor. Moreover, the study found that trading strategies based on liquidity can explain half of the profits based on momentum strategies in the same periods. The drawback of the model developed by Pástor and Stambaugh (2003) is that it is time consuming in estimation (Chen & Sherif, 2016). Marcelos and Quirós (2006) state that using the ratio developed by Amihud (2002) as an illiquidity proxy has two advantages, including a strong theory appeal and data availability. Acharya and Pedersen (2005) also found a positive shock to illiquidity in the US stock market. Similarly, Marcelo and Quirós (2006) show that aggregate illiquidity can explain stock returns in the Spanish stock market. Both Bali and Cakici (2004) and Marcelo and Quirós (2006) found positive correlations between stock returns and aggregate illiquidity.

Van der Hart et al. (2003) show that stock selections based on liquidity are inefficient (returns of illiquid stocks are not higher than returns of liquid stocks). The liquidity used in this research is the turnover ratio (the number of shares traded during the previous month divided by the total number of shares outstanding at the beginning of the month). In contrast, Chin and Nguyen (2015) found this approach works on the HSX from 2006 to 2014. Chen et al. (2019) found that buying illiquidity stocks and selling liquidity stocks in Taiwan stock markets from 1982 to 2016 can earn a 0.57 per cent premium. However, Gunathilaka et al. (2017) found a negative return in illiquidity stocks and positive returns in liquidity stocks in the Malaysian market during the post-2000 period. While the research of Chin and Nguyen (2015) uses a simple t-test to test the strategy, van der Hart et al. (2003) used both the t-test and the CAPM to benchmark the strategy. Chen et al. (2019) used the 4FM model to evaluate the strategy. Table 2.6 below shows the summary of empirical studies on illiquidity and stock returns.

Table 2.6: Empirical Studies of illiquidity

Author(s)	**Sample**	**Illiquidity Estimation**	**Findings**
Amihud (2002)	Stocks listed on NYSE, from 1964 to 1977.	The ratio of the absolute return to the trading volume.	Fama–MacBeth regressions show that stock returns and illiquidity are positively correlated. Furthermore, the illiquidity effects are stronger for small firms. Therefore, variations in the returns of these firms are related to changes in market liquidity over time.
Bali & Cakici (2004)	All nonfinancial stocks on the NYSE, AMEX, and NASDAQ,	The ratio of the absolute return to the trading volume.	Strong positive correlation between stock returns and illiquidity using Fama–

Author(s)	Sample	Illiquidity Estimation	Findings
	from 1958 to 2001.		MacBeth regressions. This is consistent with the finding of Amihud (2002).
Marcelo & Quirós (2006)	159 stocks traded on the Spanish stock market, from 1994 to 2002.	The ratio of the absolute return to the trading volume.	The Fama–MacBeth regression shows that stock returns and illiquidity are positively correlated. The alphas of the most illiquid portfolios are significantly higher than the most liquid portfolios. Therefore, illiquidity can be considered a source of risk.
Batten & Vo (2014)	All listed firms on the HSX, from 2007 to 2010.	The number of shares traded is divided by the number of shares outstanding.	Stock returns are positively correlated with liquidity, not illiquidity. This may be explained by the low integration of an emerging market like Vietnam into global markets.
Chin & Nguyen (2015)	299 listed stocks on two stock exchanges HSX and HNX in Vietnam, from 2006 to 2014.	The number of shares traded is divided by the number of shares outstanding.	Liquid portfolios have higher returns than illiquid portfolios. Investors buying liquid portfolios and selling illiquid portfolios will earn significantly positive returns.
Gunathilaka et al. (2017)	803 listed stocks on the Malaysia stock market, from 2000 to 2014.	The ratio of the absolute return to the trading volume.	Liquid portfolios have higher returns and alphas than illiquid portfolios.
Chen et al. (2019)	Stocks listed on the Taiwan and Taipei stock exchanges, from 1982 to 2016	The ratio of the absolute return to the trading volume.	Illiquid portfolios have higher returns and alphas than liquid portfolios.

This thesis tests if higher-illiquid stocks have higher returns than lower-illiquid stocks in the HSX. Therefore, the hypothesis based on illiquidity is as follows:

HA7: stock returns on the HSX have a positive relationship with illiquidity.

The positive sign of HA7 has been based on the arguments that illiquid stocks are riskier than liquid stocks, especially in situations of dire liquidity (Amihud, 2002). Therefore, investors require higher returns for illiquid stocks. Based on this hypothesis, this thesis forms trading strategies with the assumption that buying higher-illiquid stocks have higher returns than buying lower-illiquid stocks. Therefore, the arbitrage strategies that buy higher-illiquid stocks and sell lower-illiquid stocks will have positive returns.

2.5. Multifactor Models

Multifactor models use multi-sources of risks with multifactor loadings (betas) to price asset returns. These models discover predetermined factors that can explain asset returns. These risks are likely to change over time, leading to a time-varying asset return. Fama and French (1993; 1998; 2015) found that their three-factor and five-factor models are consistent with the frameworks of the ICAPM or the APT. Size factor (SMB), value factor (HML), profitability factor (RMW), and investment factor (CMA) can be used as underlying risk factors or state variables (Fama & French, 1993; 1998; 2015). While state variables are not easily recognised for empirical tests, factors are diversified portfolios that can represent unknown state variables. Common factors are represented in Table 2.7 and the following sections.

Table 2.7: Multifactor Models

Author(s)	Sample	Factors	Findings
Fama & French (1993)	Nonfinancial firms, collected from the CRSP and COMPUSTAT databases in the US, from 1963 to 1991	Three factors: • market factor • size factor • value factor.	The three-factor model, containing market, size, and value factors, explains expected stock returns. While the market factor explains stocks should have higher returns than the risk-free rate, the size and value factors explain the differences in

Author(s)	Sample	Factors	Findings
			average returns because of the differences in size and value.
Carhart (1997)	1,892 diversified equity funds, collected from Micropal/Investment Company Data (ICDI), FundScope Magazine, United Babson Reports, Wiesenberger Investment Companies and Wall Street Journal, from 1962 to 1993.	Four factors: • market factor • size factor • value factor • momentum factor.	The four-factor model has a better performance than the CAPM and the three-factor model developed by Fama & French (1993) by reducing the average pricing errors. Therefore, adding momentum as a risk factor improves the Fama–French model in explaining average stock returns.
Drew (2003)	Hong Kong, Korea, Malaysia, and the Philippines, collected from Datastream, from 1991 to 1999	Three factors: • market factor • size factor • value factor.	The pricing errors of the CAPM are larger than the three-factor model
Bali & Cakici (2004)	All nonfinancial stocks on the NYSE, AMEX, and NASDAQ, from 1958 to 2001	Five factors: • market factor • size factor • value factor • illiquidity factor • Value-at-Risk factor.	The Value-at-Risk factor adds value in explaining stock returns after controlling for market, size, value, and illiquidity factors.
Fama & French (2015)	Stocks listed on NYSE, AMEX, and NASDAQ from 1963 to 2013	Five factors: • market factor • size factor • value factor • profitability factor • investment factor.	The five-factor model explains average stock returns better than the three-factor model (Fama & French, 1993). The value factor becomes redundant after adding profitability and investment factors.
Fama and French (2017)	International stocks in 23 developed markets and divided into four regions: North America, Japan, Asia Pacific, and Europe from 1990 to 2015.	Five factors: • market factor • size factor • value factor	The value, profitability, and investment factors are strong in North America, Europe, and the Asia Pacific. In Japan, while the value factor is significant,

Author(s)	Sample	Factors	Findings
		• profitability factor • investment factor.	profitability and investment factors have little effect on stock returns. The five-factor model explains risks better than the three-factor model.
Skočir and Lončarski (2018)	3000 large companies in the US equity market from 1985 to 2016.	Eight factors: • market factor • size factor • value factor • profitability factor • investment factor • momentum factor • illiquidity factor • default risk factor.	The eight-factor model cannot explain all variations in stock returns. However, the performance of the eight-factor model is better than the three-factor and five-factor models developed by Fama and French (1993; 2015).
Hu et al. (2019)	All stocks in the Chinese A-share market, from 1995 to 2016	Three factors: • market factor • size factor • value factor.	The size factor is significant in explaining stock returns in the Chinese market. However, the market and value factors are statistically insignificant.
Hoang & Phan (2019)	351 stocks listed on the HSX, Vietnam, from 2009 to 2018	Five factors: • market factor • size factor • value factor • momentum factor • illiquidity factor.	The three-factor model developed by Fama & French (1993) is superior to the four-factor model developed by Carhart (1997). However, the best model to explain stock returns in Vietnam contains the market, size, value, and illiquidity factors.
Ryan et al. (2021)	All stocks listed on the HSX and HNX, Vietnam, from 2008 to 2015	Five factors: • market factor • size factor • value factor • profitability factor	The five-factor model developed by Fama and French is superior to their three-factor model. The value factor is not redundant in this market.

Author(s)	Sample	Factors	Findings
		• investment factor.	

2.5.1. Market Portfolio (MKT), Size Factor (SMB), and Value Factor (HML)

Fama and French (1993) developed the three-factor model (3FM) including the MKT, SMB (small minus big), and HML (high minus low). This paper opens a new approach to studying the cross-sections of stock returns by creating risk factors to explain the returns of stocks. The authors show that size and book-to-market ratios are sources of common risk factors that explain stock returns. The results of this model outperform the CAPM in the US stock market from 1963 to 1991 (Fama & French, 1993). In addition, the 3FM is popularly used in literature and many studies have found that this model is reliable in explaining cross-sectional stock returns in emerging markets in Asia and Europe (Balakrishnan, 2016; Chen et al., 2015; Rashid et al., 2018; Xie & Qu, 2016; Zaremba & Konieczka, 2015). These studies support the negative effect of size and the positive effect of value on stock returns. Cakici et al. (2016) found that the SMB cannot explain stock returns; however, the HML exists in 18 emerging stock markets in Asia, Latin America, and Europe from 1990 to 2013. In contrast, Hu et al. (2019) show a strong effect of the SMB factor in China from 1990 to 2016, while the HML factor is insignificant. Drew (2003) found that the combination of the market portfolio, size, and value factors explains stock returns in Hongkong, Korea, Malaysia, and the Philippines in the period 1991–1999. In Vietnam, Tran et al. (2013) found that the performance of the 3FM was better than the CAPM in explaining stock returns in Vietnam between 2007 and 2011, using stocks in both the HSX and HNX exchanges. This thesis also tests if these factors are sources of risk and can explain stock returns in the HSX. While Tran et al. (2013) use only six diversified Size–Value portfolios to test their model, this thesis expands the portfolio tests to 42 portfolios with different combinations.

Furthermore, the constructions of SMB and HML in this thesis are simpler using single sort rather than double sorts. Details are represented in the next chapter. Therefore, hypotheses based on the MKT, SMB, and HML factors are as follows:

> HB1: the market factor (MKT) is a systematic risk that explains stock returns in the HSX.
>
> HB2: the size factor (SMB) is a systematic risk that explains stock returns in the HSX.
>
> HB3: the value factor (HML) is a systematic risk that explains stock returns in the HSX.

2.5.2. Momentum Factor (UMD)

Carhart (1997) developed a risk model called the four-factor model (4FM) including three factors (MKT, SMB, and HML) (Fama & French, 1993) and momentum (Jegadeesh & Titman, 1993) to create the UMD (up minus down) factor to explain the performance of mutual funds in the US from 1962 to 1993. The results show that the size and momentum factors explain most of the information for average returns. More important, a strongly positive correlation between returns on the top decile funds and the one-year momentum factor is found, while there is a strong negative correlation between returns on the bottom decile and this factor. This factor is found to be strongly effective in emerging countries (Hanauer & Lauterbach, 2019; Zaremba & Konieczka, 2015). In Vietnam, Hoang and Phan (2019) show no relationship between stock returns and the UMD factor in this market between 2009 and 2018, using all stocks listed on the HSX exchange. This thesis also tests if the momentum factor is one of the sources of risk and can explain stock returns in the HSX. While Hoang and Phan (2019) used only nine diversified Size–Illiquidity portfolios to test their model, this thesis expands the portfolio tests to 42 portfolios with different combinations. Furthermore, the construction of the momentum factor in this thesis is simpler by using single sort rather than double sorts. Details are represented in the next chapter. Therefore, the hypothesis based on the UMD factor is as follows:

> HB4: the momentum factor (UMD) is a systematic risk that explains stock returns in the HSX.

2.5.3. Profitability Factor (RMW) and Investment Factor (CMA)

Lakonishok et al. (1994) claim that the book-to-market ratio is not a good indicator associated with firm characteristics. However, the authors show that value stocks produce higher returns than growth stocks. This finding is explained by the suboptimal behaviour of investors and not because of risk characteristics. Novy-Marx (2013) shows that gross profit-to-asset ratios have the same power as book-to-market ratios in predicting stock returns. In addition, controlling for profitability increases the performance of book-to-market ratios in explaining stock returns. Fama and French (2006) found a positive correlation between stock returns with both profitability and book-to-market ratio. While Fama and French (2006) used current earnings as a proxy for future profitability, Novy-Marx (2013) claims that gross profitability is a better delegation to predict stock returns. Ball et al. (2015) show that operating profitability shows far stronger than either net income or gross profit. Hou et al. (2015) found that stocks with high profitability (return on equity – ROE) gain higher returns than stocks with low profitability. In contrast, Titman et al. (2004) found a negative correlation between stock returns and capital investments. In addition, Hou et al. (2015) show that stock returns are a negative correlation with investment-to-asset ratios (I/A). Fama and French (2006; 2015) also found that higher expected rates of investment measured by lagged asset growth imply lower expected returns.

Based on the effects of profitability and investment on stock returns, Fama and French (2015) developed a five-factor model (5FM) including three factors developed in Fama and French (1993) and two new factors: RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) to capture the profitability and investment effects. In addition, Hou et al. (2015) developed a four-factor model including the market factor, size factor, investment factor, and profitability factor. The authors state that this model outperforms 3FM (Fama & French, 1993) and 4FM (Carhart, 1997). Fama and French (2017) found that value and profitability factors are stronger effects on stock returns for small stocks than for big stocks in North America, Europe, and the Asia Pacific. In contrast, the investment factor can explain average returns for small stocks only in North America. There are two differences between Fama and French (2015) and Hou et al. (2015). First, Fama and French (2015) used double-sort variables on firm size and profitability or firm size and investment to create RMW and CMA, while Hou et al. (2015) used triple-sort on firm size, I/A, and ROE to create factors. Second, the two studies used different variables as proxies for profitability and investment. Fama and French (2015) used operating profit-to-book (OP/BE) equity as a proxy for profitability and asset growth as a proxy for investment. However, Hou et al. (2015) used return on equity (ROE) as the proxy for profitability and investment-to-asset (I/A) as the proxy for investment. Leite et al. (2018) found that the 5FM performs better than the 3FM in 12 emerging markets in Latin America, Asia, and Eastern Europe from 2009 to 2017. However, the value, profitability, and investment factors are less significant than the size factor. Asad and Cheema (2017) found that the q-factor model developed by Hou et al. (2015) tends to outperform the CAPM (Sharpe, 1964), the 3FM (Fama & French, 1993), and the 4FM (Carhart, 1997). Recently, Ryan et al. (2021) found that the 5FM model explains risks better than the 3FM model in Vietnam using stocks in both the HSX and the HNX exchanges.

This thesis also tests if the profitability and investment factors are the sources of risks and can explain stock returns in the HSX. While Ryan et al. (2021) used 27 diversified portfolios with three combinations of firm size and firm value, firm size and profitability, firm size and investment to test their model, this thesis expands the portfolio tests to 42 portfolios with different combinations. Furthermore, the constructions of the profitability and investment factors in this thesis are simpler using single sort rather than double sorts. Details are represented in the next chapter. Therefore, hypotheses based on the RMW and CMA are as follows:

> HB5: the profitability factor (RMW) factor is a systematic risk that explains stock returns in the HSX.
>
> HB6: the investment factor (CMA) is a systematic risk that explains stock returns in the HSX.

2.5.4. Illiquidity (HILLIQL), VaR (HVaRL), and CVaR (LCVaRH) Factors

Amihud et al. (2015) found that the illiquidity is priced in 45 countries, including 19 emerging markets and 25 developed markets in three regions: the Americas, Asia Pacific, and Europe. In particular, the returns of illiquid stocks in emerging markets are higher than returns in developed markets. Marcelo and Quirós (2006) found that adding the illiquidity factor into the 3FM (Fama & French, 1993) improves the performance of the model. Bali and Cakici (2004) found that the size factor, illiquidity factor, and Value-at-Risk factor are systematic risks and explain stock returns in the US market. Although these papers measured illiquidity using the method developed by Amihud (2002), the factor is constructed differently. While Marcelo and Quirós (2006) follow the approach of Fama and French (1993) by using double sort variables: size and illiquidity ratio to create the factor. Bali and Cakici (2004) and Amihud et al. (2015) developed zero-investment illiquidity factors (high illiquidity minus low illiquidity) directly from the illiquidity ratio developed by Amihud (2002) using the median breakpoint and quintile breakpoints, respectively. Batten and Vo (2014) show that liquidity measured by the turnover does not affect stock returns in the HSX from 2007 to 2010 in stock levels. According to the authors, this discrepancy may be originated from the low connection of this market to global markets. Tran et al. (2013) found that the combination of 3FM and liquidity factor (equal-weighted return of low illiquid portfolios minus high illiquid portfolios) can explain stock returns in the Vietnamese stock market from 2007 to 2011. This thesis also tests if the illiquidity factor is one of the sources of risks and can explain stock returns in the HSX. While Tran et al. (2013) measured the liquidity factor from the average traded value in a month and the ratio of the number of shares traded to the number of shares outstanding, this thesis measures the illiquidity factor from the ratio of the absolute return to the trading volume. Furthermore, while Tran et al. (2013) used only six diversified Size–Value portfolios to test their model, this thesis expands the portfolio tests to 42 portfolios with different combinations. Therefore, the hypothesis based on the HILLIQL are as follows:

> HB7: the illiquidity factor (HILLIQL) factor is a systematic risk that explains stock returns in the HSX.

Bali and Cakici (2004) created a VaR factor called HVaRL (high VaR minus low VaR) and the authors found that both VaR and HVaRL are positively correlated with returns at both stock and portfolio levels. Similar to the formation of the HILLIQL, the HVaRL is created directly from VaR. In contrast, Trimech and Benammou (2012) show a negative correlation between portfolio returns and VaR in the French market. In addition, Chen et al. (2014) found that this factor is more effective in emerging markets than in developed markets. Mselmi et al. (2019) found that portfolios including non-distressed stocks were rewarded for bearing VaR risk in the French market from 1998 to 2012. In Vietnam, there are limited studies on the VaR factor. This thesis tests if the VaR factor is one of the sources of risks and can explain stock returns in the HSX using the single-sort approach of Bali and Cakici (2004). Hence, the hypothesis based on the Value-at-Risk factor is as follows:

> HB8: the Value-at-Risk factor (HVaRL) factor is a systematic risk that explains stock returns in the HSX.

VaR was found to be enhanced by CVaR to measure tail risks (Abad et al., 2014; Artzner et al., 1999; Unbreen & Sohail, 2020; Uryasev, 2000). Although both methods measured losses, they do not have a similar effect on stock returns. While stock returns and VaR were found to be positively correlated (Aziz & Ansari, 2017; Bali & Cakici, 2004; Bali et al., 2007), stock returns and CVaR were found to be negatively correlated (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019). Based on this negative relation, this thesis assumes that lower-CVaR stocks have higher returns than higher-CVaR stocks because they are rewarded by higher risk. Therefore, this thesis develops the conditional Value-at-Risk as a risk factor and the hypothesis as follows:

> HB9: the conditional Value-at-Risk factor (LCVaRH) factor is a systematic risk that explains stock returns in the HSX.

In the end, this thesis tests nine risk factors for the HSX. These factors in this research are different from the model built in Skočir and Lončarski (2018) in terms of the way that factors are built up, variable measurements, number of risk factors, and samples for testing. This study form factors directly from characteristic variables; however, Skočir and Lončarski (2018) depended on double sort variables developed by Fama and French (1993; 2015). While Skočir and Lončarski (2018) built the liquidity factor based on Pástor and Stambaugh (2003), this research measures the illiquidity factor developed by Amihud (2002). Skočir and Lončarski (2018) tested their model in the developed market (the US) while this thesis tests the model in a developing market (Vietnam). Drew and Veeraraghavan (2002), Ragab et al. (2020) state that developing markets have different economic and market structures compared to developed markets. Therefore, this thesis can add an out-of-sample test to the literature. In addition, van der Hart et al. (2003) describe emerging markets as being more illiquid than developed markets. Hence, using illiquidity as a variable is more appropriate for HSX, an emerging market. Furthermore, this research studies the effect of Value-at-Risk and conditional Value-at-Risk as new risk measurements that are not represented in Skočir and Lončarski (2018). Moreover, Skočir and Lončarski (2018) used 25 portfolios for each combination between size and other using quintiles. In contrast, because of the small sample with 100 stocks in the HSX, this research uses the median as the breakpoint for size, 30th and 70th percentiles for other variables. This forms the seven portfolios for each combination between Size–Value, Size–Static Beta, Size–Dynamic Beta, Size–Momentum, Size–Illiquidity, Size–VaR, and Size–CVaR. Thus, 42 portfolios are created for testing factor models.

2.5.5. Factor Construction

Multifactor models use arbitrage portfolios to create factors. For example, Fama and French (1993) used two sort variables including market value and book-to-market ratio to create the SMB (small size minus big size) and HML (high-value minus low-value) factors to capture the size and value effects in stocks returns and create the three-factor model (3FM). Similarly, based on the 3FM, Carhart (1997) used market value, and momentum sorts to create UMD (up momentum minus down momentum) to capture the momentum effect and create the four-factor model (4FM). Fama and French (2015) created the five-factor model which uses market value and profitability sorts, market value, and investment sorts to create RMW (robust minus weak profitability) and CMA (conservative minus aggressive investment) to capture the profitability and investment effects, respectively. Hou et al. (2015) used triple sorts on size, investment-to-assets, and return on equity (ROE) to construct the q-factor model. However, for a small sample of stocks, this approach will decrease the number of stocks in each portfolio and lessen the effect of risk diversification (Skočir & Lončarski, 2018). In contrast, Bali and Cakici (2004) used a single sort including illiquidity ratio and Value-at-Risk to create HILLIQL (high illiquidity minus low illiquidity) and HVaRL (high Value-at-Risk minus low Value-at-Risk) respectively to create factors. The authors combined both single sort and double sorts in their research.

In this thesis, I justify and make common risk factors simpler by using a single sort variable to create factors and this is expected to get similar effects. According to Harvey et al. (2016), a risk factor should be a variable that cannot be predicted through time. In addition, risk exposures of assets to this factor can explain the cross-sections of stock returns. Therefore, if a firm characteristic is correlated with the cross-sectional returns, a long-short portfolio can be formed to represent the underlying unknown risk factor.

2.6. Testing Asset Pricing Models

Fama and MacBeth (1973) developed a regression to explain the cross-section of stock returns. This regression is often used to study the relationship between asset returns and their firm characteristics (Fama & French, 1992; 2006; Hanauer & Lauterbach, 2019; Novy-Marx, 2013). This technique can be applied directly to stock-level data, and it is based on assumptions of normal distribution of variables and the linearity between asset returns and the independent variables. However, estimated variables using historical data can be caused "errors-in-variables" when applying this regression. For example, beta stocks are estimated using historical data of asset returns and market returns, they have sampling errors. This method uses two-step estimations (Fama & French, 1992; Fama & MacBeth, 1973; Jagannathan & Wang, 2002). First, run cross-sectional OLS regression between asset returns and other firm characteristics that can explain the returns of assets. Second, test the time-series coefficients using a t-test if they are different from zero. If a t-statistic of a coefficient is significant, the cross-sectional relation between asset return and firm characteristics is confirmed after monitoring for the effects of other independent variables.

Claessens et al. (1995) state that the “between-estimator technique” can decrease this error by the averaging process. In other words, this technique takes the average of the data before running the OLS and it can capture the cross-sectional information in the data (Claessens et al., 1995; Croissant & Millo, 2018). This technique uses regression of average asset returns on the average values of other independent variables such as betas. Claessens et al. (1995) explain that if one of the explanatory variables is measured with error, this technique automatically decreases the bias which is called the errors-in-variable automatically through the averaging procedure.

The Fama–MacBeth technique is standard in testing asset pricing models using cross-sectional regressions because its advantages carry over to panels (time series of cross-sections). The slopes in the regression are monthly returns whose average values can be used to test the cross-sectional relations between stock returns and other variables (Fama, 2014). However, when autocorrelation between the coefficients exists, correcting the standard errors of the average slopes is recommended (Fama, 2014; Millo, 2017; 2019; Petersen, 2009; Thompson, 2011).

An asset pricing model can be tested using time series (Black et al., 1972; Fama & French, 1993). A factor model is efficient when the intercept (the alpha) of that model should be zero for all equations (Black et al., 1972; Gibbons et al., 1989; Merton, 1973). However, the BJS test (Black et al., 1972) use univariate t statistics for each equation. In contrast, the GRS test (Gibbons et al., 1989) developed a multivariate generalisation of the univariate t-test that allows testing all alphas equal to zero simultaneously. The authors suggest that the multivariate test can bring more appropriate inferences than using a set of dependent univariate statistics. The GRS test is often used to evaluate the performance of linear factor models (Fama & French, 1993; 1998; 2012; 2015; Skočir & Lončarski, 2018). The Fama–

MacBeth and panel regressions use firm characteristics to explain stock returns while the time series method use factors at portfolio levels to test this correlation. The advantage of using portfolios and time series is that the factor can be used to explain all assets like bonds. In contrast, using firm levels cannot do that, for example, bonds do not have the book-to-market ratio like stocks (Fama & French, 1993).

2.7. Conclusion

This chapter represents the literature on asset pricing both individual stock level (firm characteristics) and portfolio level (risk factors). Different characteristics and risk factors are found to be related to stock returns. The empirical studies show mixed results in both emerging and developed markets. Some characteristics have similar effects in both markets while some characteristics show different results in different countries and different regions. The differences may be caused by the different economic structures (Ragab et al., 2020). Furthermore, some characteristics reduce effects over time. This may be caused by the replication of arbitrageurs in their trading after characteristics are publicised (Jacobs & Müller, 2020). Testing financial anomalies in Vietnam provide a new and out-of-sample test to the finance literature by using data in an emerging market that is not integrated like those in developed markets. This empirical study can reduce the "home bias" and "foreign bias" (Hanauer & Lauterbach, 2019). Based on the literature review in this chapter, the next chapter reconstructs existing factor risks in a simpler way using a single sort to appropriate with the small sample in emerging markets. Based on the recent finding of the cross-section between CVaR and stock returns, the next chapter develops a CVaR factor called LCVaRH. Reconstruction of existing risk factors and adding new ones provide new methods for the literature. The next chapter also provides appropriate strategies for selecting stocks for investors based on different characteristics and risk factors for the HSX.

Chapter 3: Methodologies

3.1. Introduction

In Chapter 2, the finance literature shows that stock returns are correlated with not only systematic risk (beta), but also firm characteristics. Therefore, the CAPM model cannot fully explain stock returns. This chapter is designed to provide a quantitative framework that works with real data on the HSX to test the hypotheses in Chapter 2. First, the chapter introduces a conceptual framework. Next, the sample size is defined with the formula for each variable used in the research for both stock level and portfolio level. Then, hypotheses are tested for firm characteristics (HA1 to HA7) to understand the correlation between stock returns and firm characteristics. Similarly, multifactor models are tested to find appropriate risk factors for the HSX (hypotheses HB1 to HB9). The last part tests different stock selections (A to O) based on the understanding of the cross-section of stock returns and firm characteristics (HA1 to HA7) so that they bring the highest returns and alpha (the intercept of multifactor models) for investors in this market.

3.2. Conceptual Framework

The research is based on the cross-section of stock returns and the alpha of multi-factor models to select appropriate trading strategies for the HSX. From Chapter 2, stock returns are hypothesised that positively correlated with CAPM beta (Fama & MacBeth, 1973; Sharpe, 1964), DCC beta (Bali et al., 2017; Engle, 2002), firm value (value) (Alhashel, 2021; Fama & French, 1992; Hanauer & Lauterbach, 2019), momentum (Fama & French, 2012; Singh & Walia, 2021; Wang et al., 2021), VaR (Aziz & Ansari, 2017; Chen et al., 2014; Iqbal & Azher, 2014), and illiquidity (Amihud et al., 2015; Chen et al., 2019; Gunathilaka et al., 2017). In contrast, stock returns are assumed to be negatively correlated with firm size (size) (Alhashel, 2021; Fama & French, 1992; Vasishth et al., 2021) and CVaR (Ling &

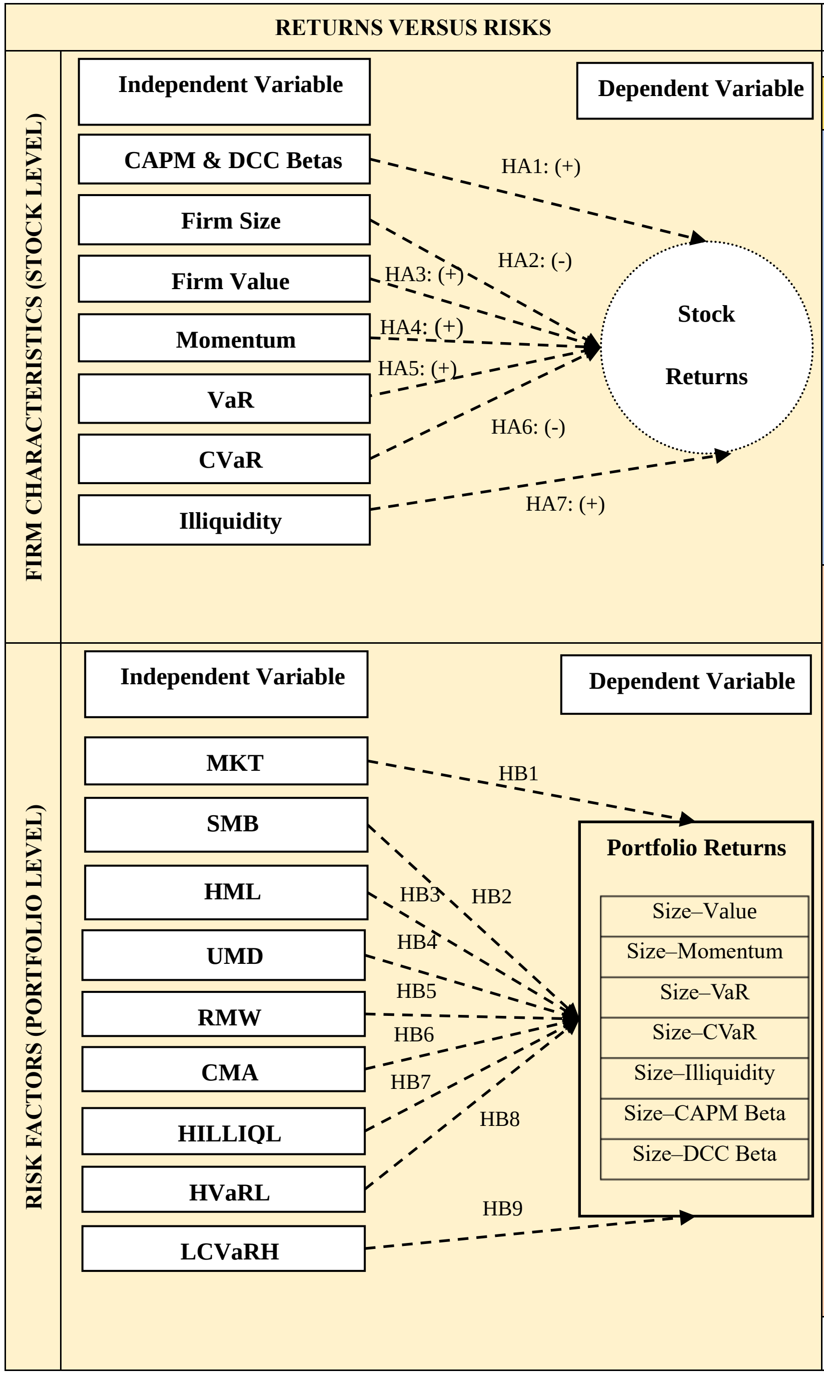
Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019). These cross-sections of stock returns are tested for the HSX, equivalent to hypotheses HA1 to HA7. Fama (2014) states that the Fama–MacBeth regression (FM) is standard in studying cross-correlation issues. The author also states that the benefit of FM estimation is to run regression on panel data instead of regressing average stock returns on other variables using between estimators (BE). However, Claessens et al. (1995) state that BE estimation can overcome the limitation called errors-in-variables of the FM approach. This thesis uses different estimations including Fama–MacBeth (FM) regression, between estimators (BE), ordinary least squares (OLS), fixed effects (FE), and random effects (RE) to test relations between stock returns and their firm characteristics in the HSX.

Next, multifactor models (portfolio level) are studied to select risk factors that can explain the most risk for this market. Sharpe (1964) found that only market risk (the fluctuation of market portfolio, MKT) affects stock returns in the CAPM model. However, Fama and French (1993) show that adding size factor (SMB) and value factor (HML) can improve the performance of the CAPM. Recently, hundreds of factors have been found to be significant in explaining stock returns in different markets and periods (Harvey & Liu, 2019; Harvey et al., 2016). In this thesis, nine risk factors are tested containing the market portfolio (MKT) (the hypothesis HB1), size factor (SMB) (the hypothesis HB2), value factor (HML) (the hypothesis HB3), momentum factor (UMD) (the hypothesis HB4), profitability factor (RMW) (the hypothesis HB5), investment factor (CMA) (the hypothesis HB6), illiquidity factor (HILLIQL) (the hypothesis HB7), VaR factor (HVaRL) (the hypothesis HB8), and the CVaR factor (LCVaRH) (the hypothesis HB9) to select appropriate risk factors for the HSX. Researchers often use 25 portfolios created by the quintile size and quintile value to test multifactor models (Bali & Cakici, 2004; Fama & French, 1993). This thesis uses different portfolios created by the firm size (size) median and 30th and 70th percentiles of other variables containing the firm value (value), momentum, VaR, CVaR, illiquidity, CAPM beta, and DCC beta to test risk models. Therefore, different portfolios containing Size–Value portfolios, Size–Momentum portfolios, Size–VaR portfolios, Size–CVaR portfolios, Size–Illiquidity portfolios, Size–CAPM beta portfolios, and Size–DCC beta portfolios are constructed to test the nine risk factors. Theoretically, risk factors should explain stock returns for all assets; therefore, using different portfolios to test risk factors to see that these factors can survive outside Size – Value portfolios. Moreover, the alpha (intercept) of the best model is used to evaluate the performance of an investment.

The information of the first and the second studies are premises for building and testing related trading strategies. Both single-sort and double-sort variables are studied. For single sort analyses, from the analysis of firm characteristics, stocks are selected into three portfolios based on CAPM beta, DCC beta, Size, Value, Momentum, Value-at-Risk (VaR), conditional Value-at-Risk (CVaR), and Illiquidity using 30th and 70th percentiles of firm characteristics. For double sort analyses, the first sort variable is the firm size and the median breakpoint is applied to separate stocks into two groups small size and big size. The second sort variable is firm value, momentum, VaR, CVaR, illiquidity, CAPM beta, or DCC beta, respectively. Thirtieth and 70th percentiles are applied for these characteristics to separate into three groups: high, medium, or low. Therefore, six portfolios are created for each combination between size and another characteristic. Then excess returns of these portfolios are tested over time from January 2011 to December 2019 (108 months). Furthermore, this thesis tests the returns of different portfolios based on the firm characteristics in the same period to figure out what portfolios and strategies bring higher returns for investors in the HSX. Based on the relations between stock returns and their characteristics from HA1 to HA7, two trading strategies are applied for each stock selection, including long and arbitrage strategies. The trading strategies are based on both single-sort and double-sort variables.

Each stock selection using a single sort variable contains two strategies: long and arbitrage while using double sort variables, each stock selection contains four strategies: two long and two arbitrage strategies.

The assumptions from HA1 to HA7 indicate that long strategies expected to have higher returns and higher alphas are buying smaller-size stocks (portfolios), buying higher-value stocks (portfolios), buying higher-momentum stocks (portfolios), buying higher-VaR stocks (portfolios), buying lower-CVaR stocks (portfolios), buying higher-illiquid stocks (portfolios), buying higher-CAPM beta stocks (portfolios), and buying higher-DCC beta stocks (portfolios). Furthermore, arbitrage strategies expected to have higher returns and higher alphas are buying smaller-size stocks (portfolios) and selling bigger-size stocks (portfolios), buying higher-value stocks (portfolios) and selling lower-value stocks (portfolios), buying higher-momentum stocks (portfolios) and selling lower-momentum stocks (portfolios), buying higher-VaR stocks (portfolios) and selling lower-VaR stocks (portfolios), buying lower-CVaR stocks (portfolios) and selling higher-CVaR stocks (portfolios), buying higher-illiquid stocks (portfolios) and selling lower-illiquid stocks (portfolios), buying higher-CAPM beta stocks (portfolios) and selling lower-CAPM beta stocks (portfolios), and buying higher-DCC beta stocks (portfolios) and selling lower-DCC beta stocks (portfolios). Figure 3.1 below shows the conceptual framework of this thesis.



STOCK SELECTIONS FOR TRADING STRATEGIES

	STOCK SELECTIONS	TRADING STRATEGIES	TESTING
SINGLE SORT VARIABLE	Size (A)	- A1: Long Smaller-Size Portfolios - A2: Long Smaller-Size – Short Bigger-Size Portfolios	- t-test - Alpha
	Value (B)	- B1: Long Higher-Value Portfolio - B2: Long Higher-Value – Short Lower-Value Portfolios	- t-test - Alpha
	Momentum (C)	- C1: Long Higher-Momentum Portfolio - C2: Long Higher-Momentum – Short Lower-Momentum Portfolios	- t-test - Alpha
	VaR (D)	- D1: Long Higher-VaR Portfolio - D2: Long Higher-VaR – Short Lower-VaR Portfolios	- t-test - Alpha
	CVaR (E)	- E1: Long Lower-CVaR Portfolios - E2: Long Lower-CVaR – Short Higher-CVaR Portfolios	- t-test - Alpha
	Illiquidity (F)	- F1: Long Higher-Illiquid Portfolios - F2: Long Higher-Illiquidity – Short Lower-Illiquidity Portfolios	- t-test - Alpha
	CAPM Beta (G)	- G1: Long Higher-CAPM Beta Portfolios - G2: Long Higher-CAPM Beta – Short Lower-CAPM Beta Portfolios	- t-test - Alpha
	DCC Beta (H)	- H1: Long Higher-DCC Beta Portfolios - H2: Long Higher-DCC Beta – Short Lower-DCC Beta Portfolios	- t-test - Alpha
DOUBLE SORT VARIABLES	Size–Value (I)	- I1: Long Smaller-Size Portfolios - I2: Long Higher-Value Portfolios - I3: Long Smaller-Size – Short Bigger-Size Portfolios - I4: Long Higher-Value – Short Lower-Value Portfolios	- t-test - Alpha
	Size–Momentum (J)	- J1: Long Smaller-Size Portfolios - J2: Long Higher-Momentum Portfolios - J3: Long Smaller-Size – Short Bigger-Size Portfolios - J4: Long Higher-Momentum – Short Lower-Momentum Portfolios	- t-test - Alpha
	Size–VaR (K)	- K1: Long Smaller-Size Portfolios - K2: Long Higher-VaR Portfolios - K3: Long Smaller-Size – Short Bigger-Size Portfolios - K4: Long Higher-VaR – Short Lower-VaR Portfolios	- t-test - Alpha
	Size–CVaR (L)	- L1: Long Smaller-Size Portfolios - L2: Long Lower-CVaR Portfolios - L3: Long Smaller-Size – Short Bigger-Size Portfolios - L4: Long Lower-CVaR – Short Higher-CVaR Portfolios	- t-test - Alpha
	Size–Illiquidity (M)	- M1: Long Smaller-Size Portfolios - M2: Long Higher-Illiquid Portfolios - M3: Long Smaller-Size – Short Bigger-Size Portfolios - M4: Long Higher-Illiquidity – Short Lower-Illiquidity Portfolios	- t-test - Alpha
	Size–CAPM Beta (N)	- N1: Long Smaller-Size Portfolios - N2: Long Higher-CAPM Beta Portfolios - N3: Long Smaller-Size – Short Bigger-Size Portfolios - N4: Long Higher-CAPM Beta – Short Lower-CAPM Beta Portfolios	- t-test - Alpha
	Size–DCC Beta (O)	- O1: Long Smaller-Size Portfolios - O2: Long Higher-DCC Beta Portfolios - O3: Long Smaller-Size – Short Bigger-Size Portfolios - O4: Long Higher-DCC Beta – Short Lower-DCC Beta Portfolios	- t-test - Alpha

Figure 3.1: Conceptual Framework

3.3. Sample Data

The sample includes the 100 largest non-financial stocks selected from approximately 400 listed stocks on the HSX from 2011 to 2019. Using non-financial stocks will remove the high leverage of these companies which indicates financial distress (Fama & French, 1992). In addition, Vo (2016) states that financial companies have different nature of business compared to non-financial companies. Therefore, dead companies, banks, financial services, and investment firms are excluded from the sample. The research needs at least 24 months of stock returns to estimate CAPM beta and Value-at-Risk; therefore, data is collected from 2009. In addition, because the HSX was established in 2000 and experienced the financial crisis in 2007 and 2008, the data collection started in 2009 is expected to remove the biases of this event. These stocks are selected by sorting all listed stocks on HSX using their market capitalisation at the end of the year 2019. Data are collected from the Eikon database and Vietstock, a public website on financial data in Vietnam. This thesis uses 100 stocks to reduce the computations and estimation. At the end the sample is the panel with 100 stocks over 108 months, approximately 10,800 computations for each variable. A large dynamic covariance matrix is created by the DCC GARCH to estimate dynamic beta. This is challenging and time consuming for a personal computer to run the method.

3.4. Variables

There are two types of data in this research: individual stock data and portfolio data. For the study on firm characteristics, individual stock data are used to study the cross-section of stock returns and their firm characteristics. The dependent variable is the monthly stock return, while the independent variables are CAPM beta, DCC beta, firm size, firm value, momentum, VaR, CVaR, and illiquidity. For the study on risk factors (portfolio level), portfolio data are used to build and test multifactor models. The dependent variables are portfolio returns of Size–CAPM beta, Size–DCC beta, Size–Value, Size–Momentum, Size–VaR, Size–CVaR, and Size–Illiquidity portfolios. Independent variables are returns of different risk factors including the MKT, SMB, HML, UMD, HVaRL, LCVaRH, HILLIQL, RMW, and CMA. For the study on stock selection, portfolio data formed by firm characteristics are used for both parametric and nonparametric methods to find what portfolios bring a higher positive return for investors.

3.4.1. Stock Level

3.4.1.1. Monthly Stock Returns

The monthly returns are the net returns which are calculated from the adjusted daily closing prices (Eikon item P.HC) (the price after adjustments for any corporate actions, such as stock splits, dividends, and right offerings) of the last trading days at the end of each month. Therefore, returns computed from adjusted closing prices include dividends. This research uses net returns to be in line with portfolio analysis because portfolio returns are calculated from net returns, but not log returns. Excess monthly returns are returns after deducting the risk-free rate. The ten-year government bond rate (Eikon item TRVNZ10Y) is represented as the risk-free rate.

$$R_{i,t} = \left(\frac{P_{i,t}}{P_{i,t-1}}\right) - 1 \tag{1}$$

$$R_{m,t} = \left(\frac{I_{m,t}}{I_{m,t-1}}\right) - 1 \tag{2}$$

$$r_{i,t} = R_{i,t} - R_f \tag{3}$$

Where:

$P_{i,t}$: adjusted closing price of stock i at the end of month t

$P_{i,t-1}$: adjusted closing price of stock i at the end of month t–1

$I_{m,t}$: VN index at the end of month t

$I_{m,t-1}$: VN index at the end of month t–1

$R_{i,t}$: the monthly return of stock i at the end of month t

$R_{m,t}$: the monthly return of the VN index at the end of month t

R_f: risk-free rate

$r_{i,t}$: the excess return of stock i at the end of month t

3.4.1.2. Market Beta

The CAPM beta measures the systematic risk of the sample (Sharpe, 1964). CAPM beta estimation can be used differently in the periodicity of data including daily, weekly, monthly, or yearly (Bali et al., 2016; 2017). However, beta is significantly biased when using daily returns on infrequently traded stocks (Dimson, 1979; Handa et al., 1989; Scholes & Williams, 1977). To tackle this issue, this thesis uses monthly returns to estimate beta (Ali & Badhani, 2021; De Giorgi et al., 2019; Hanauer & Lauterbach, 2019). Moreover, logarithmic returns are used to reduce the effect of thin trading (Fowler et al., 1979). Because the sample is small, beta is estimated using OLS over 24 to 36 months (inclusive) returns of stock and market.

$$Ln(1 + R_{i,t}) = \alpha_{i,t} + \beta_{i,t}^{CAPM} Ln(1 + R_{m,t}) + \varepsilon_{i,t} \quad (4)$$

Where:

$Ln(1 + R_{i,t})$: continuously compounded return of stock i at the end of month t

$Ln(1 + R_{m,t})$: continuously compounded return of VN-index at the end of month t

$\alpha_{i,t}$: alpha coefficient of stock i for month t

$\beta_{i,t}^{CAPM}$: CAPM beta coefficient of stock i for month t

$\varepsilon_{i,t}$: residual of stock i for month t

Thin trading adjustments for beta using OLS are found statistically insignificant in Australia between 1995 and 1999 (Davidson & Josev, 2005) and in the US between 1963 and 2013 (Bali et al., 2017). In contrast, the dynamic betas based on the DCC model show a positive correlation with stock returns (Bali et al., 2017; Engle, 2002). Although the CAPM betas change each month because the research uses monthly rolling regressions, they are constant over a window of 24–36 months. In contrast, DCC betas change monthly. The advantage of the DCC beta over the CAPM beta is that the DCC beta has a dynamic feature that puts more weight on recent observations and it varies each month in the estimation period; however, the CAPM beta is constant within an estimation window (Bali et al., 2017). While Bali et al. (2017) used daily data to estimate DCC betas, this thesis uses monthly data to reduce the effect of thin trading. This thesis uses the historical excess monthly returns from December 2010 to December 2019 to estimate the DCC betas for 100 stocks and the market portfolio (Bali et al., 2009).

$$R_{i,t+1} - R_{f,t+1} = \alpha_0^i + \sigma_{i,t+1} u_{i,t+1} \tag{5}$$

$$R_{m,t+1} - R_{f,t+1} = \alpha_0^m + \sigma_{m,t+1} u_{m,t+1} \tag{6}$$

$$\sigma_{i,t+1}^2 = \beta_0^i + \beta_1^i \sigma_{i,t}^2 u_{i,t}^2 + \beta_2^i \sigma_{i,t}^2 \tag{7}$$

$$\sigma_{m,t+1}^2 = \beta_0^m + \beta_1^m \sigma_{m,t}^2 u_{m,t}^2 + \beta_2^m \sigma_{m,t}^2 \tag{8}$$

$$\sigma_{im.t+1} = \rho_{im,t+1} \sigma_{i,t+1} \sigma_{m,t+1} \tag{9}$$

$$\rho_{im,t+1} = \frac{q_{im,t+1}}{\sqrt{q_{ii,t+1} q_{mm,t+1}}} \tag{10}$$

$$q_{im,t+1} = \bar{\rho}_{im} + a_1\left(u_{i,d}u_{m,t} - \bar{\rho}_{im}\right) + a_2\left(q_{im,t} - \bar{\rho}_{im}\right) \quad (11)$$

$$u_{i,t} = \frac{\varepsilon_{i,t}}{\sigma_{i,t}} \quad (12)$$

$$u_{m,t} = \frac{\varepsilon_{m,t}}{\sigma_{m,t}} \quad (13)$$

$$\beta_{i,t+1}^{DCC} = \frac{\sigma_{im,t+1}}{\sigma_{m,t+1}^2} \quad (14)$$

Where:

$R_{i,t+1} - R_{f,t+1}$: excess return of stock i at the end of month t+1

$R_{m,t+1} - R_{f,t+1}$: excess return of the VNI at the end of month t+1

$\sigma_{i,t+1}^2$: conditional variance of stock i in month t+1

$\sigma_{m,t+1}^2$: conditional variance of the VNI in month t+1

$\sigma_{im,t+1}$: conditional covariance between stock i and the VNI in month t+1

$\rho_{im,t+1}$: conditional correlation between stock i and the VNI in month t+1

$\bar{\rho}_{im}$: unconditional correlation between stock i and the VNI

$u_{i,t}$: the standardised residuals for stock i in month t

$u_{m,t}$: the standardised residuals for the VNI in month t

$\beta_{i,t+1}^{DCC}$: dynamic conditional beta of stock i in month t+1

3.4.1.3. Firm Size and Firm Value

The firm size and firm value are the natural logarithms of market value and the book-to-market ratio of stocks, respectively (Fama & French, 1992). The book value of a stock is calculated at the end of December of year t–1 and the market value is the previous monthly market value at year t. The book value of a stock is the result of the book value per share (Eikon item WC05491) multiplied by the number of shares outstanding (Eikon item WC05301) at the company's fiscal year-end. The market value (Eikon item MV) is updated monthly. For example, to find the firm value of stock i of month j in year t, the book value at the end of year t–1 and the market value of month j–1 in year t are used for computation.

$$\mathrm{Size}_{i,t} = \mathrm{Ln}\left(\mathrm{MV}_{i,t-1}\right) \tag{15}$$

$$\mathrm{BV}_{i,t-1} = \mathrm{BVPS}_{i,t-1} \text{ x } \mathrm{N}_{i,t-1} \tag{16}$$

$$\mathrm{BTM}_{i,t} = \frac{\mathrm{BV}_{i,t-1}}{\mathrm{MV}_{i,t-1}} \tag{17}$$

$$\mathrm{Value}_{i,t} = \mathrm{Ln}\left(\mathrm{BTM}_{i,t}\right) \tag{18}$$

Where:

$\mathrm{MV}_{i,t-1}$: market value of stock i at the end of month t–1

$\mathrm{Size}_{i,t}$: the firm size of stock i at the end of month t

$\mathrm{BV}_{i,t-1}$: book value of stock i at the end of year t–1

$\mathrm{BVPS}_{i,t-1}$: book value per share of stock i at the end of year t–1

$\mathrm{N}_{i,t-1}$: number of shares outstanding of stock i at the end of year t–1

$\mathrm{BTM}_{\mathrm{i,t}}$: book-to-market equity ratio of stock i at the end of month t

$\mathrm{Value}_{\mathrm{i,t}}$: the firm value of stock i at the end of month t

3.4.1.4. Momentum

The momentum of a stock is the product of gross returns in the previous 11 months and excludes month t (the current month) to separate the medium-term momentum from the reversal effect of short-term momentum (Bali et al., 2016; Jegadeesh & Titman, 1993). Jegadeesh and Titman (1993) show that the past 12-month cumulative returns are highly positively correlated with stock returns. In addition, Bali et al. (2016) found that excluding the current stock return from the computation of momentum separates the medium-term momentum calculated from the past 11-month cumulative from the short-term reversal effect calculated from the current month t of stock returns.

$$\mathrm{Mom}_{\mathrm{i,t}} = 100\left[\prod_{\mathrm{t-11}}^{\mathrm{t-1}}\left(\mathrm{R}_{\mathrm{i,t}} + 1\right) - 1\right] \quad (19)$$

Where:

$\mathrm{Mom}_{\mathrm{i,t}}$: the momentum of stock i at the end of month t

$\mathrm{R}_{\mathrm{i,t}}$: the monthly return of stock i at the end of month t

3.4.1.5. VaR

This thesis estimates VaR from monthly historical returns. A window of 24–36 months (inclusive), and a confidence level of 95 per cent are used to calculate VaR (Aziz & Ansari, 2017). First, the 5 per cent quantile of the monthly return $r_{i,t}$ (the left tail, negative) is determined as follows:

$$P\left(R_{i,t} < r_{i,t}\right) = 5\% \quad (20)$$

Then a monthly VaR is multiplied by negative 1 to measure the downside risk (Bali & Cakici, 2004; Bali et al., 2007):

$$VaR_{i,t} = -r_{i,t} \tag{21}$$

Where:

P: probability

$r_{i,t}$: the quantile equivalent to 5% chance to lose $r_{i,t}$ on month t

$VaR_{i,t}$: monthly VaR of stock i at the end of month t

VaR determines how much the value of a stock return decrease over time with a given probability. The estimation uses the past 24–36 monthly returns to estimate VaR from the left tail (5%) of the actual distribution. Bali et al. (2009) state that the original VaR is negative because it is calculated from the left tail of the distribution, but the downside risk ($VaR_{i,t}$) is defined as this VaR multiplied by negative one before running regressions.

Conditional VaR is the average loss exceeding VaR. A window of 24–36 months (inclusive), and a confidence level of 95 per cent are used to calculate CVaR. Similar to VaR, CVaR is multiplied by negative 1. The formula to calculate CVaR is as follows:

$$CVaR_{i,t} = -E[R_{i,t}|R_{i,t} < r_{i,t}] \tag{22}$$

Where:

$CVaR_{i,t}$: monthly CVaR of stock i at the end of month t

Both VaR and CVaR are popularly used as risk management tools (Guo et al., 2019). However, CVaR is reported better performance than VaR (Artzner et al., 1999; Rockafellar & Uryasev, 2000; Unbreen & Sohail, 2020; Uryasev, 2000).

3.4.1.6. Illiquidity

The monthly illiquidity of a stock is the ratio of the total absolute value of daily returns divided by the daily dollar volume traded in the security, average over trading days in each month (Amihud, 2002). The daily value volume traded of stock i on day d is calculated as the adjusted closing price (Eikon item P. HC) of the stock times the number of shares traded (Eikon item VO) in Vietnamese currency (dong). The illiquidity in this research is using the logarithmic form to overcome the skewness in the data. The calculation is as follows:

$$\mathrm{Illiq}_{i,t} = \mathrm{Ln}\left[\frac{1}{D}\sum_{1}^{D}\frac{|R_{i,d}|}{\mathrm{Vold}_{i,d}}\right] \tag{23}$$

Where:

$\mathrm{Illiq}_{i,t}$: Illiquidity of stock i in month t

$R_{i,d}$: the daily return of stock i on day d in the previous month

$\mathrm{Vold}_{i,d}$: value volume traded of stock i on day d in the previous month in billion dong

D: number of trading days in the previous month

Table 3.1: Summary of Individual Variables

Variables	**Notation**	**Data**	**Estimation**
Monthly stock returns	R_i	Monthly adjusted prices (Eikon item P.HC)	Net returns
Risk-free rate	R_f	10-year government bond rate (Eikon item TRVNZ10Y)	
Excess monthly stock returns	r_i	Monthly stock returns Risk-free rate	Monthly stock returns minus the risk-free rate

Variables	Notation	Data	Estimation
Market returns	R_m	VN-index returns (Eikon item HCMNVNE)	Net returns
CAPM beta	βCAPM	Monthly stock returns Risk-free rate Market returns	OLS
DCC beta	βDCC	Monthly stock returns Risk-free rate Market returns	DCC GARCH
Firm size	$Size_i$	Market value (Eikon item MV)	The logarithm of market value
Firm value	$Value_i$	Book value: book value per share (Eikon item WC05491) id multiplied by the number of shares outstanding (Eikon item WC05301) Market value (Eikon item MV)	The logarithm of the book-to-market ratio
Momentum	Mom_i	Monthly stock returns: net returns calculated from the monthly adjusted closing prices (Eikon item P.HC)	Cumulative returns of the past 11 months.
VaR	VaR_i	Monthly stock returns: net returns calculated from the monthly adjusted closing prices (Eikon item P.HC)	Nonparametric (5% VaR)
CVaR	$CVaR_i$	Monthly stock returns: net returns calculated from the monthly adjusted closing prices (Eikon item P.HC)	Nonparametric method (5% CVaR)
Illiquidity	$Illiq_i$	Daily returns: net returns calculated from the daily adjusted closing prices (Eikon item P.HC) Daily value volume traded: number of shares traded (Eikon item VO) multiplied by the adjusted closing prices (Eikon item P.HC)	The ratio of the absolute return to the trading volume.

3.4.2. Portfolio Level

3.4.2.1. MKT, SMB, and HML Factors

MKT is the return of the market portfolio and the VN-index (Eikon item HCMNVNE), a value-weighted index, is used as the MKT. The MKT is used in the market model and this is the only source of risk to calculate the CAPM beta. In addition, the MKT is used in multifactor models to explain why average stock returns are above the risk-free rate (Fama & French, 1993).

SMB (small size minus big size) and HML (high value minus low value) developed by Fama and French (1993) are the size-mimicking and value-mimicking portfolios, respectively. While Fama and French (1993) use double sort including market capitalisation (size) and book-to-market ratio (value) to develop these factors, this thesis reconstructs SMB and HML using single sort directly from firm size and firm value. At the end of December each year, stocks are grouped into two-size portfolios (small size and big size using size median) and two-value portfolios (low value and high value using value median). The return of the SMB is the difference between the average value-weighted returns of the small-size portfolio and the average value-weighted returns of the big-size portfolio. Similarly, the return of the HML is the difference between the average value-weighted returns of the high-value portfolio and the average value-weighted returns of the low-value portfolio. The computations are as follows:

$$\mathrm{MKT_t} = \mathrm{R_{m,t}} - \mathrm{R_f} \tag{24}$$

$$\mathrm{SMB}_t = S_t - B_t \tag{25}$$

$$\mathrm{HML}_t = H_t - L_t \tag{26}$$

Where:

$\mathrm{MKT_t}$: the excess return of market portfolio (VN-index) at the end of month t

$\mathrm{SMB_t}$: return of the SMB factor in month t

$\mathrm{HML_t}$: return of the HML factor in month t

$\mathrm{S_t}$: return of the small-size portfolio in month t

$\mathrm{B_t}$: return of the big-size portfolio in month t

$\mathrm{H_t}$: return of the high-value portfolio (high book-to-market ratio) in month t

L_t: return of the low-value portfolio (low book-to-market ratio) in month t

3.4.2.2. UMD, RMW, and CMA Factors

UMD (up momentum minus down momentum) is developed by Carhart (1997) using double sort variables containing size and momentum. However, this thesis reconstructs UMD using a single sort directly from momentum. RMW (robust operating profitability minus weak operating profitability) and CMA (conservative investment minus aggressive investment) are developed by Fama and French (2015). Fama and French (1993) use double sort including size and operating profitability, size and investment to develop RMW and CMA, respectively. In contrast, this thesis reconstructs RMW and CMA using a single sort directly from operating profitability and investment.

Operating profitability (OP) is calculated at the end of December of year t–1 as revenues (Rev) minus items including cost of goods sold (COGS); selling, general, and administrative expenses (SGA); interest expense (IE), and the result is divided by book value (BV). Investment (I) is the change of total assets (TA) from the end of December of year t–2 to the end of December of year t–1, divided by total assets at the end of year t–2. The detailed computations are as follows:

$$\mathrm{OP}_{i,t} = \frac{Rev_{i,t-1} - COGS_{i,t-1} - SGA_{i,t-1} - IE_{i,t-1}}{BE_{i,t-1}} \quad (27)$$

$$I_{i,t} = \frac{TA_{i,t-1} - TA_{i,t-2}}{TA_{i,t-2}} \quad (28)$$

Where:

$OP_{i,t}$: operating profit of stock i at the end of year t

$Rev_{i,t-1}$: revenue of stock i at the end of year t–1

$COGS_{i,t-1}$: cost of goods sold of stock i at the end of year t–1

$SGA_{i,t-1}$: selling, general, and administrative expenses of stock i in year t–1

$IE_{i,t-1}$: interest expense of stock i in year t–1

$I_{i,t}$: investment of stock i at the end of year t

$TA_{i,t-2}$: total asset of stock i at the end of year t–2

$TA_{i,t-1}$: total asset of stock i at the end of year t–1

HVaRL (high Value-at-Risk minus low Value-at-Risk) is based on the development of Bali and Cakici (2004) using a single sort variable directly from Value-at-Risk. LCVaRH is the conditional Value-at-Risk risk mimicking factor. Based on recent findings that CVaR is negatively correlated with stock returns (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019), LCVaRH is constructed by taking the differences between the return of the low-CVaR portfolio and the return of the high-CVaR portfolios. UMD, HVaRL, and LCVaRH are constructed by using a single sort variable. Details of these portfolios are as follows:

At the end of December each year, stocks are grouped into two momentum portfolios (up momentum and down momentum using the momentum median). Likewise, the return of the RMW is the difference between the average value-weighted returns of the robust-profitability portfolio and the average value-weighted returns of the weak-profitability portfolio. In contrast, the return of the CMA is the difference between the average value-weighted returns of the conservative investment portfolio and the average value-weighted returns of the aggressive investment portfolio. The computations are as follows:

$$\mathrm{UMD}_t = U_t - D_t \tag{29}$$

$$\mathrm{RMW}_t = Robust_t - Weak_t \tag{30}$$

$$\mathrm{CMA}_t = Conservative_t - Aggressive_t \tag{31}$$

Where:

$\mathrm{UMD_t}$: return of UMD factor in month t

$\mathrm{U_t}$: return of the portfolio with up momentum in month t

$\mathrm{D_t}$: return of the portfolio with down momentum in month t

$\mathrm{RMW_t}$: return of the RMW factor in month t

$\mathrm{CMA_t}$: return of the CMA factor in month t

$\mathrm{Robust_t}$: return of the robust–profitability portfolio in month t

$\mathrm{Weak_t}$: return of the weak–profitability portfolio in month t

$\mathrm{Conservative_t}$: the return of the conservative–investment portfolio in month t

$\mathrm{Aggressive_t}$: the return of the aggressive–investment portfolio in month t

3.4.2.3. HILLIQL, HVaRL, and LCVaRH Factors

HILLIQL (high illiquidity minus low illiquidity) is based on the development of Bali and Cakici (2004) using a single sort directly from illiquidity. HVaRL (high Value-at-Risk minus low Value-at-Risk) is based on the development of Bali and Cakici (2004) using a single sort variable directly from Value-at-Risk. LCVaRH is the conditional Value-at-Risk risk mimicking factor. Based on recent findings that CVaR is negatively correlated with stock returns (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019), LCVaRH is constructed by taking the differences between the return of the low-CVaR portfolio and the return of the high-CVaR portfolios. UMD, HVaRL, and LCVaRH are constructed by using a single sort variable. Details of these portfolios are followed.

At the end of December each year, stocks are grouped into two illiquidity portfolios (high illiquidity and low illiquidity using the illiquidity median), two Value-at-Risk portfolios (high Value-at-Risk and low Value-at-Risk using the Value-at-Risk median), and two conditional Value-at-Risk portfolios (high conditional Value-at-Risk and low conditional Value-at-Risk using conditional Value-at-Risk median). The return of the HILLIQL is the difference between the average value-weighted returns of the high-illiquidity portfolio and the average value-weighted returns of the low-illiquidity portfolio. Likewise, the return of the HVaRL is the difference between the average value-weighted returns of the high-VaR portfolio and the average value-weighted returns of the low-VaR portfolio. In contrast, the return of the LCVaRH is the difference between the average value-weighted returns of the low-CVaR portfolio and the average value-weighted returns of the high-CVaR portfolio. The computations are as follows:

$$\mathrm{HILLIQL}_t = \mathrm{HILLIQ}_t - \mathrm{LILLIQ}_t \tag{32}$$

$$\mathrm{HVaRL}_t = \mathrm{HVaR}_t - \mathrm{LVaR}_t \tag{33}$$

$$\mathrm{LCVaRH}_t = \mathrm{LCVaR}_t - \mathrm{HCVaR}_t \tag{34}$$

Where:

$\mathrm{HILLIQL_t}$: return of HILLIQL factor in month t

$\mathrm{HILLIQ_t}$: return of the high–illiquidity portfolio in month t

$\mathrm{LILLIQ_t}$: return of the low–illiquidity portfolio in month t

$\mathrm{HVaRL_t}$: return of HVaRL factor in month t

$\mathrm{HVaR_t}$: return of the high–VaR portfolio in month t

$\mathrm{LVaR_t}$: return of the low–VaR portfolio in month t

$\mathrm{LCVaRH_t}$: return of LCVaRH factor in month t

$\mathrm{LCVaR_t}$: return of the low–CVaR portfolio in month t

$\mathrm{HCVaR_t}$: return of the high–CVaR portfolio in month t

Table 3.2: Summary of Risk Factors

Factors	Notation	Breakpoints
Size	SMB	Median of firm size (logarithm of market capitalisation)
Value	HML	Median of firm value (logarithm of book-to-market ratio)
Momentum	UMD	Median of momentum (cumulative returns of the past 11 months)
Profitability	RMW	Median of operating profitability
Investment	CMA	Median of investment (asset growth)
Illiquidity	HIILIQL	Median of illiquidity (the ratio of the absolute return to the trading volume)
Value-at-Risk (VaR)	HVaRL	Median of VaR (nonparametric, 5% VaR)
Conditional Value-at-Risk (CVaR)	LCVaRH	Median of CVaR (nonparametric, 5% CVaR)

3.4.2.4. Portfolio Returns

Size–Value, Size–Momentum, Size–VaR, Size–CVaR, Size–Illiquidity, Size–CAPM Beta, and Size–DCC Beta are portfolios created by combining size and value, momentum, Value-at-Risk, conditional Value-at-Risk, illiquidity, CAPM beta, or DCC beta, respectively. Size is grouped into two portfolios including small size and big size using the median as the breakpoint. Other variables are grouped into three portfolios including the low (down) group, medium (neutral) group, or high (up) group using 30th and 70th percentiles. Therefore, each combination creates six portfolios, and 42 portfolios are created in total. Returns of these portfolios are average value-weighted returns. The details of these portfolios are shown in Table 3.3 below.

Table 3.3: Summary of Portfolio Returns

<table>
<tr><th>Sort</th><th>Breakpoint</th><th>Portfolios</th></tr>
<tr><td>2 × 3 sort on Size and Value</td><td>Size: median
Value: 30th and 70th percentiles</td><td><table><tr><td>Value
Size</td><td>High</td><td>Medium</td><td>Low</td></tr><tr><td>Small</td><td>SH</td><td>SM</td><td>SL</td></tr><tr><td>Big</td><td>BH</td><td>BM</td><td>BL</td></tr></table></td></tr>
<tr><td>2 × 3 sort on Size and Momentum</td><td>Size: median
Momentum: 30th and 70th percentiles</td><td><table><tr><td>Momentum
Size</td><td>Up</td><td>Neutral</td><td>Down</td></tr><tr><td>Small</td><td>SU</td><td>SN</td><td>SD</td></tr><tr><td>Big</td><td>BU</td><td>BN</td><td>BD</td></tr></table></td></tr>
<tr><td>2 × 3 sort on Size and Value-at-Risk (VaR)</td><td>Size: median
VaR: 30th and 70th percentiles</td><td><table><tr><td>VaR
Size</td><td>High</td><td>Medium</td><td>Low</td></tr><tr><td>Small</td><td>SHVaR</td><td>SMVaR</td><td>SLVaR</td></tr><tr><td>Big</td><td>BHVaR</td><td>BMVaR</td><td>BLVaR</td></tr></table></td></tr>
<tr><td>2 × 3 sort on Size and Conditional Value-at-Risk (CVaR)</td><td>Size: median
CVaR: 30th and 70th percentiles</td><td><table><tr><td>CVaR
Size</td><td>High</td><td>Medium</td><td>Low</td></tr><tr><td>Small</td><td>SHCVaR</td><td>SMCVaR</td><td>SLCVaR</td></tr><tr><td>Big</td><td>BHCVaR</td><td>BMCVaR</td><td>BLCVaR</td></tr></table></td></tr>
<tr><td>2 × 3 sort on Size and Illiquidity</td><td>Size: median
Illiquidity: 30th and 70th percentiles</td><td><table><tr><td>Illiquidity
Size</td><td>High</td><td>Medium</td><td>Low</td></tr><tr><td>Small</td><td>SHIlliq</td><td>SMIlliq</td><td>SLIlliq</td></tr><tr><td>Big</td><td>BHIlliq</td><td>BMIlliq</td><td>BLIlliq</td></tr></table></td></tr>
</table>

<table>
<tr><th>Sort</th><th>Breakpoint</th><th>Portfolios</th></tr>
<tr><td>2 × 3 sort on Size and CAPM beta</td><td>Size: median
CAPM beta: 30th and 70th percentiles</td><td><table>
<tr><td>CAPM Beta / Size</td><td>High</td><td>Medium</td><td>Low</td></tr>
<tr><td>Small</td><td>SHCAPM</td><td>SMCAPM</td><td>SLCAPM</td></tr>
<tr><td>Big</td><td>BHCAPM</td><td>BMCAPM</td><td>BLCAPM</td></tr>
</table></td></tr>
<tr><td>2 × 3 sort on Size and DCC beta</td><td>Size: median
DCC beta: 30th and 70th percentiles</td><td><table>
<tr><td>DCC Beta / Size</td><td>High</td><td>Medium</td><td>Low</td></tr>
<tr><td>Small</td><td>SHDCC</td><td>SMDCC</td><td>SLDCC</td></tr>
<tr><td>Big</td><td>BHDCC</td><td>BMDCC</td><td>BLDCC</td></tr>
</table></td></tr>
</table>

3.5. Analytical Methods

3.5.1. Descriptive Statistics

3.5.1.1. Stock Returns and Firm Characteristics

This study summarises fundamental statistics including mean, standard deviation, skewness, excess kurtosis, min and max values of monthly stock return, CAPM beta, DCC beta, size, value, momentum, Value-at-Risk, and illiquidity. Then the distribution of the variables is plotted and tested if they are normal distributions. Next, the correlation between these variables is computed to find out where is a strong or weak relationship between the variables.

3.5.1.2. Portfolio Returns and Risk Factors

This study summarises fundamental statistics including mean, standard deviation, skewness, excess kurtosis, min and max values of monthly portfolio returns, MKT, SMB, HML, UMD, HVaRL, LCVaRH, HILLIQL, RMW, and CMA. Then, the distribution of the variables is plotted and tested if they are normal distributions. Next, the correlation between these variables is computed to find out where is a strong or weak relationship between the variables.

3.5.2. Firm Characteristics and Stock Returns in the HSX

3.5.2.1. Estimations

This study tests six hypotheses: HA1, HA2, HA3, HA4, HA5, HA6, and HA7 to understand the effect of CAPM beta, DCC beta, size, value, momentum, Value-at-Risk, conditional Value-at-Risk, and illiquidity, respectively on monthly stock returns for the HSX. Many papers use Fama–Macbeth regression (Amihud, 2002; Fama & French, 1992; Fama & MacBeth, 1973; Hanauer & Lauterbach, 2019; Lakonishok et al., 1994; Marcelo & Quirós, 2006). Although this methodology is not based on the assumption of the normal distribution of errors and can apply to small samples, it has a limitation called errors-in-variables (Bhandari, 1988). The between-estimators estimation is found to avoid bias in Fama–MacBeth regression (Claessens et al., 1995). Moreover, the Fama–MacBeth regression and between-estimator technique allow these betas are updated periodically and priced (Bhandari, 1988; Claessens et al., 1995; Fama & MacBeth, 1973). Because panel regressions have problems of residual covariance and autocorrelation, robustness using Newey and West (1987) and clustering techniques are applied (Fama, 2014; Millo, 2017; 2019; Petersen, 2009; Thompson, 2011).

It is well known that pool regression is not consistent if there exists a correlation between the error term and the lagged endogenous variable because of an individual effect (Croissant & Millo, 2018). Panel data econometrics allows controlling for unobserved heterogeneity which may cause bias in estimation. This advantage leads to more efficiency in coefficient estimations and improves measurement accuracy (Croissant & Millo, 2018). This research applies the Fama–MacBeth regression (FM), between-estimators model (BE), pool regression (OLS), fixed effects (FE), and random effects (RE). To separate the effect of CAPM beta and DCC beta, VaR, and CVaR, two models (1a) and (1b) below are studied. In addition, firm size, firm value, momentum, Value-at-Risk and illiquidity are included (Amihud, 2002; Bali & Cakici, 2004; Fama & French, 1992; Jegadeesh & Titman, 1993). The between model transforms variables of the panel into individual means (Claessens et al., 1995; Fama, 2014). The pool regression is the OLS regression that is applied to the raw panel data. The fixed effects will demean the variables of the panel so that the individual effects will be disappeared. In contrast, the random effects consider the individual effects as random which are generated from a specific distribution. The individual effects are the correlation between the residuals of a given firm across months or years, while the time effects are the correlation between the residuals of a given year across different stocks (Millo, 2019). These effects can be estimated by the panel regressions. More details on panel data analyses using R software are mentioned in Croissant and Millo (2018). The regressions using monthly data are as follows:

$$\mathrm{R}_{\mathrm{i,t+1}} = \gamma_0 + \gamma_1 \beta_{\mathrm{i,t}}^{CAPM} + \gamma_3 \mathrm{Size}_{\mathrm{i,t}} + \gamma_4 \mathrm{Value}_{\mathrm{i,t}} + \gamma_5 \mathrm{Mom}_{\mathrm{i,t}} + \gamma_6 \mathrm{VaR}_{\mathrm{i,t}} + \gamma_7 \mathrm{Illiq}_{\mathrm{i,t}} + \varepsilon_{\mathrm{i}} \qquad (35)$$

$$\mathrm{R}_{\mathrm{i,t+1}} = \gamma_0 + \gamma_2 \beta_{\mathrm{i,t}}^{DCC} + \gamma_3 \mathrm{Size}_{\mathrm{i,t}} + \gamma_4 \mathrm{Value}_{\mathrm{i,t}} + \gamma_5 \mathrm{Mom}_{\mathrm{i,t}} + \gamma_6 \mathrm{CVaR}_{\mathrm{i,t}} + \gamma_7 \mathrm{Illiq}_{\mathrm{i,t}} + \varepsilon_{\mathrm{i}} \qquad (36)$$

3.5.2.2. Test the Multicollinearity

In econometrics, multicollinearity is a phenomenon when one independent variable in a multiple regression model is linear with other independent variables. When high multicollinearity happens, this may cause invalid results. Therefore, a variable with high multicollinearity with others should be removed from the regression model. To detect multicollinearity, the research uses the variance inflation factor (VIF) introduced by Wooldridge (2012). When VIF is greater than 10, it is high multicollinearity.

3.5.2.3. Test the Normal Distribution of Residuals

To test the normal distribution of the residuals, the research uses the Jarque–Bera test (Tsay, 2012). The null hypothesis of the test is that the residuals are normally distributed. Therefore, if the p-value is less than the chosen alpha (1%, 5%, or 10% levels), the null hypothesis will be rejected. Otherwise, the null hypothesis will be accepted.

3.5.2.4. Test the Serial Correlation

The serial correlation happens when the residuals of a given stock may be correlated across months (time-series dependence) (Petersen, 2009; Wooldridge, 2012). This study uses the Breusch–Godfrey test (Millo, 2019; Wooldridge, 2012) to assess the autocorrelation of the residuals in the two models (1a) and (1b). The null hypothesis is that no serial correlation is detected in the errors. If the p-value is less than the chosen alpha (1%, 5%, and 10% levels), the null hypothesis will be rejected. Otherwise, the null hypothesis will be accepted.

3.5.2.5. Test the Cross-Sectional Dependence (CD)

Different from the serial correlation, cross-sectional dependence happens when the residuals of a given month may be correlated across different stocks (Croissant & Millo, 2018; Millo, 2017; Petersen, 2009). This study uses the Breusch-Pagan and Perasan CD tests (Croissant & Millo, 2018) to assess the cross-sectional dependence of the residuals in the two models (1a) and (1b). If the p-value is less than the chosen alpha (1%, 5%, or 10% levels), the cross-sectional dependence is detected. Otherwise, there is no cross-sectional dependence.

3.5.2.6. Robustness

If there are correlations in residuals, two robustness techniques are applied. The traditional approach uses a method developed by Newey and West (1987) to enhance the standard deviation of the coefficients in the models (Millo, 2017; 2019; Petersen, 2009; Wooldridge, 2012). Another approach uses clustering. Because a panel data is created on two different dimensions including entities (stocks) and time (months), clustering methods including individual clustering, time clustering, or double clustering are applied to correct the standard errors of estimated coefficients (Millo, 2017; 2019; Petersen, 2009; Thompson, 2011). While the method developed by Newey and West (1987) only corrects the correlation across time, the clustering techniques can correct the correlation across entities using individual clustering or the correlation across time using time clustering or corrections in both dimensions using both individual and time clusterings. Therefore, the new clustering techniques will be superior to the traditional method for panel econometrics (Millo, 2019; Petersen, 2009; Sun et al., 2018).

3.5.2.7. Fixed Effects versus Random Effects

To determine whether the models are fixed effects or random effects, the Hausman test is applied (Croissant & Millo, 2018). The null hypothesis of the Hausman test is that the random effects are preferred to the fixed effects. If the p-value is less than the chosen alpha (1%, 5%, or 10% levels), the random effects are rejected. Otherwise, the random effects are accepted.

3.5.2.8. Individual Effects versus Time Effects versus Both Effects

To determine whether the models are individual effects, time effects, or both effects, F tests are applied (Croissant & Millo, 2018). To test the presence of individual effects, time effects, or both effects, the F test compares the nested models OLS (no effects) and panel regressions with individual effects, time effects, and both effects, respectively. If the p-value is less than the chosen alpha (1%, 5%, or 10% levels), the OLS (no effects) is rejected and panel regressions with individual effects, time effects, or both effects are more appropriate. Otherwise, the OLS is more appropriate. To test the absence of individual effects but allow for the presence of time effects, the F test compares the nested panel regressions: individual effects and both effects. If the p-value is less than the chosen alpha (1%, 5%, or 10% levels), both effects are more appropriate than individual effects. Otherwise, the individual effects are more appropriate. To test the absence of time effects but allow for the presence of individual effects, the F test compares the nested panel regressions: time effects and both effects. If the p-value is less than the chosen alpha (1 percent, 5 percent, or 10 percent levels), both effects are more appropriate than time effects. Otherwise, the time effects are more appropriate.

3.5.3. Testing Risk Factors in the HSX

3.5.3.1. Selected Risk Factors

The three-factor model (3FM) (Fama & French, 1993), four-factor model (4FM) (Carhart, 1997; Fama & French, 1993), and five-factor model (5FM) (Fama & French, 2015) are frequently used to test the correlation between portfolios returns and risk factors in finance literature. Fama and French (1993) show that stock returns have little relation to CAPM beta; however, the 3FM with market factor, size factor, and value factor can explain this relationship. Carhart (1997) found that 4FM can explain most of the variation in returns of mutual funds. In addition, Fama and French (2015) state that 3FM is an incomplete model to explain expected returns. The authors show that 3FM misses much of the variation related to profitability and investment and a 5FM model brings better performance than the 3FM. Therefore, factor models keep developing more factors in the future. This thesis studies nine risk factors containing the market factor (MKT), size factor (SMB), value factor (HML), momentum factor (UMD), Value-at-Risk factor (HVaRL), conditional Value-at-Risk factor (LCVaRH), illiquidity factor (HILLIQL), profitability factor (RMW), and investment factor (CMA). Fama and French (1993) show that if there exist multiple risk factors in stock returns, the slopes of risk factors in the model below should be significant when running regressions with the market portfolio (MKT). The illustration is as follows:

$$\mathrm{MKT_t} = \alpha + \beta F_t + \varepsilon_{i,t} \tag{37}$$

Where:

F_t: return of factor F in month t

For example, if the SMB and HML exist in stock returns the slopes of these factors are significant when regressed with the MKT. This is applied to 4FM, 5FM, and other factor models developed to explain stock returns. Therefore, selected risk factors (F_t) are the subset of the nine factors that the slopes are significant using model 2. Because multifactor models use different risk factors, there may exist multicollinearity. This problem is detected by VIF.

3.5.3.2. Multifactor Models

In the finance literature, the methodology of Fama and French (1993) using 25 portfolios mixing a quintile of size and a quintile of value is popular for testing factor models (Bali & Cakici, 2004; Fama & French, 1993; 2015). However, the sample of stocks in the HSX is small (100 stocks); therefore, this research uses six portfolios that are adopted from the study of Trimech and Benammou (2012). These portfolios are created by combining size and value using the median as the breakpoint for size, 30th and 70th percentiles as breakpoints for value to test the models including the SH portfolio (small size and high value), SM portfolio (small size and medium value), SL portfolio (small size and low value), BH portfolio (big size and high value), BM portfolio (big size and medium value), and BL portfolio (big size and low value). In addition, the research expands the tests to other portfolios including six Size–Momentum portfolios, six Size–VaR portfolios, six Size–CVaR portfolios, six Size–Illiquidity portfolios, six Size–CAPM beta portfolios, and six Size–DCC beta portfolios. These portfolios are created as similar to the six Size–Value portfolios using median breakpoint for size and 30th and 70th percentiles as breakpoints for other variables. The multifactor models are represented in the model below:

$$R_{P,t} = \alpha + \beta F_t + \varepsilon_{i,t} \quad (38)$$

Where:

$R_{p,t}$: return of portfolio p at the end of month t

P: portfolios combined by size and value, momentum, VaR, CVaR, illiquidity, CAPM, DCC betas

3.5.3.3. GRS Test

To determine which model is efficient, researchers often test if the intercepts in a set of time-series regressions are all zeros using the GRS test (Fama & French, 2015; Gibbons et al., 1989; Hou et al., 2015; Jagannathan & Wang, 2002).

3.5.4. Stock Selections for Trading Strategies

Van der Hart et al. (2005; 2003) use excess returns and zero-investment returns of different value and momentum portfolios to evaluate the profitability of trading strategies. The authors tested the returns of these portfolios over time using a t-test and the alpha of the market model and the 4FM. Following this approach and based on the hypotheses in the previous study, the thesis extends the tests to different stock selections that are based on firm size, firm value, momentum, Value-at-Risk, conditional Value-at-Risk, illiquidity, CAPM beta, and DCC beta. In each theme, two main trading strategies are formed including long and arbitrage strategies. First, in each month, stock returns are sorted using a single sort variable based on firm characteristics or double sort variables with the first sort being firm size and the second sort being firm value, momentum, VaR, CVaR, illiquidity, CAPM beta, or DCC beta. The next step is to form portfolios.

For single sort variable, stocks are divided into three size portfolios, three value portfolios, three momentum portfolios, three VaR portfolios, three CVaR portfolios, three illiquidity portfolios, three CAPM beta, and three DCC beta using 30th and 70th percentiles of these characteristics, respectively. For double sort variables, stocks are divided into two groups small and big using the size median. Stocks also are divided into three value groups, three momentum groups, three Value-at-Risk groups, three conditional Value-at-Risk groups, three CAPM beta groups, and three DCC beta groups using the 30th and 70th percentiles of these characteristics. Therefore, six Size–Value portfolios, six Size–Momentum portfolios, six Size–VaR portfolios, six Size–CVaR portfolios, six Size–Illiquidity portfolios, six Size–CAPM beta portfolios, and six Size–DCC beta portfolios are created. T-tests are applied to excess returns or returns of arbitrage portfolios to test different strategies based on both single-sort and double-sort analyses. To detect heteroscedasticity in time series, the technique developed by Newey and West (1987) is applied to adjust the standard errors caused by autocorrelation and heteroscedasticity. If there exists a monocity pattern in a strategy, that strategy is effective, and the strategy is recommended for investors in the HSX. This study is used as a nonparametric approach. An advantage of this technique is no assumptions about the distributions of variables. To control for risk mimicking portfolios in the factor models, the research uses the alpha coefficient. Alpha is the intercept in a factor model whose dependent variables are excess monthly portfolio returns or monthly returns of arbitrage portfolios and independent variables are monthly returns of common risk factors. If alpha is significantly positive, assets are undervalued, and investors should buy them. Otherwise, assets are overvalued, and investors should sell them.

For a single sort variable, stocks are sorted by Size, Value, Momentum, Value-at-Risk, Conditional Value-at-Risk, Illiquidity, CAPM beta, and DCC beta using the 30th and 70th percentiles of these characteristics. Therefore, three size portfolios, three value portfolios, three momentum portfolios, three VaR portfolios, three CVaR portfolios, 3 illiquidity portfolios, 3 CAPM beta portfolios, and 3 DCC beta portfolios are created. Then based on the cross-section of stock returns and firm characteristics (HA1 to HA7), appropriate trading strategies are created as follows:

3.5.4.1. Strategies Based on Firm Size (A)

Long strategies (A1): Buying smaller-size stocks should have higher returns than buying bigger-size stocks:

- Buying small-size stocks (S stocks with a size less than or equal to the 30th percentile) should have a higher return than buying medium-size stocks (M stocks with a size greater than or equal to the 30th percentile and less than or equal to the 70th percentile).
- Buying medium-size stocks should have a higher return than buying big-size stocks (B – stocks with a size greater than or equal to the 70th percentile).

Arbitrage strategies (A2): Buying smaller-size stocks and selling bigger-size stocks should have positive returns:

- Buying small-size stocks and selling medium-size stocks (S–M).
- Buying small-size stocks and selling big-size stocks (S–B).
- Buying medium-size stocks and selling big-size stocks (M–B).

3.5.4.2. Strategies Based on Firm Value (B)

Long strategies (B1): Buying higher-value stocks should have higher returns than buying lower-value stocks:

- Buying low-value stocks (L stocks with a book-to-market ratio less than or equal to the 30th percentile) should have a lower return than buying medium-value stocks

(M stocks with a book-to-market ratio greater than or equal to the 30th percentile and less than or equal to the 70th percentile).

- Buying medium-value stocks should have a lower return than buying high-value stocks (H stocks with a book-to-market ratio greater than or equal to the 70th percentile).

Arbitrage strategies (B2): Buying higher-value stocks and selling lower-value stocks should have positive returns:

- Buying high-value stocks and selling low-value stocks (H–L).
- Buying high-value stocks and selling medium-value stocks (H–M).
- Buying medium-value stocks and selling low-value stocks (M–L).

3.5.4.3. Strategies Based on Momentum (C)

Long strategies (C1): Buying higher-momentum stocks should have higher returns than buying lower-momentum stocks:

- Buying down-momentum stocks (D stocks with a momentum less than or equal to the 30th percentile) should have a lower return than buying neutral-momentum stocks (N stocks with a momentum greater than or equal to the 30th percentile and less than or equal to the 70th percentile).
- Buying neutral-momentum stocks should have a lower return than buying up-momentum stocks (U stocks with a momentum greater than or equal to the 70th percentile).

Arbitrage strategies (C2): Buying higher-momentum stocks and selling lower-momentum stocks should have positive returns:

- Buying up-momentum stocks and selling down-value stocks (U–D).

- Buying up-momentum stocks and selling neutral-momentum stocks (U–N).
- Buying neutral-momentum stocks and selling down-momentum stocks (N–D).

3.5.4.4. Strategies Based on Value-at-Risk (D)

Long strategies (D1): Buying higher-VaR stocks should have higher returns than buying lower-VaR stocks:

- Buying low-VaR stocks (LVaR stocks with a Value-at-Risk less than or equal to the 30th percentile) should have a lower return than buying medium-VaR stocks (MVaR stocks with a Value-at-Risk greater than or equal to the 30th percentile and less than or equal to the 70th percentile).
- Buying medium-VaR stocks should have a lower return than buying high-VaR stocks (HVaR stocks with a Value-at-Risk greater than or equal to the 70th percentile) have the highest return.

Arbitrage strategies (D2): Buying higher-VaR stocks and selling lower-VaR stocks should have positive returns:

- Buying high-VaR stocks and selling low-Var stocks (HVaR–LVaR).
- Buying high-VaR stocks and selling medium-VaR stocks (HVaR–MVaR).
- Buying medium-VaR stocks and selling low-VaR stocks (MVaR–LVaR).

3.5.4.5. Strategies Based on Conditional Value-at-Risk (E)

Long strategies (E1): Buying lower-CVaR stocks should have higher returns than buying higher-CVaR stocks:

- Buying low-CVaR stocks (LCVaR stocks with a conditional Value-at-Risk less than or equal to the 30th percentile) should have a higher return than buying medium-CVaR stocks (MCVaR stocks with a conditional Value-at-Risk greater than or equal to the 30th percentile and less than or equal to the 70th percentile).

- Buying medium-CVaR stocks should have a higher return than buying high-CVaR stocks (HCVaR stocks with a conditional Value-at-Risk greater than or equal to the 70th percentile) have the lowest return.

Arbitrage strategies (E2): Buying lower-CVaR stocks and selling higher-CVaR stocks should have positive returns:

- Buying low-CVaR stocks and selling medium-CVar stocks (LCVaR–MCVaR).
- Buying low-CVaR stocks and selling high-CVaR stocks (LCVaR–HCVaR).
- Buying medium-CVaR stocks and selling high-CVaR stocks (MCVaR–HCVaR).

3.5.4.6. Strategies Based on Illiquidity (F)

Long strategies (F1): Buying higher-illiquid stocks should have higher returns than buying lower-illiquid stocks:

- Buying low-illiquid stocks (Lilliq stocks with illiquidity less than or equal to the 30th percentile) should have a lower return than buying medium-illiquid stocks (Milliq stocks with illiquidity greater than or equal to the 30th percentile and less than or equal to the 70th percentile).
- Buying medium-illiquid stocks should have a lower return than buying high-illiquid stocks (Hilliq stocks with illiquidity greater than or equal to the 70th percentile).

Arbitrage strategies (F2): Buying higher-illiquid stocks and selling lower-illiquid stocks should have positive returns:

- Buying high-illiquid stocks and selling low-illiquidity stocks (HIlliq–LIlliq).
- Buying high-illiquid stocks and selling medium-illiquid stocks (HIlliq–MIlliq).

- Buying medium-illiquid stocks and selling low-illiquid stocks (MIlliq–LIlliq).

3.5.4.7. Strategies Based on CAPM Beta (G)

Long strategies: Buying higher-CAPM stocks should have higher returns than buying lower-CAPM stocks:

- Buying low-CAPM beta stocks (LCAPM stocks with a CAPM beta less than or equal to the 30th percentile) should have a lower return than buying medium – CAPM beta stocks (MCAPM stocks with a CAPM beta greater than or equal to the 30th percentile and less than or equal to the 70th percentile).
- Buying medium-CAPM beta stocks should have a lower return than buying high-CAPM beta stocks (HCAPM stocks with a CAPM beta greater than or equal to the 70th percentile).

Arbitrage strategies (G2): Buying higher-CAPM stocks and selling lower-CAPM stocks should have positive returns:

- Buying high-CAPM beta stocks and selling low-CAPM beta stocks (HCAPM–LCAPM).
- Buying high-CAPM beta stocks and selling medium-CAPM beta stocks (HCAPM–MCAPM).
- Buying medium-CAPM beta stocks and selling low-CAPM beta stocks (MCAPM–LCAPM).

3.5.4.8. Strategies Based on DCC Beta (H)

Long strategies (H1): Buying higher-DCC stocks should have higher returns than buying lower-DCC stocks:

- Buying low-DCC beta stocks (LDCC stocks with a DCC beta less than or equal to the 30th percentile) should have a lower return than buying medium-DCC beta stocks (MDCC stocks with a DCC beta greater than or equal to the 30th percentile and less than or equal to the 70th percentile).
- Buying medium-DCC beta stocks should have a lower return than buying high-DCC beta stocks (HDCC stocks with a DCC beta greater than or equal to the 70th percentile).

Arbitrage strategies (H2): Buying higher-DCC stocks and selling lower-DCC stocks should have positive returns:

- Buying high-DCC beta stocks and selling low-DCC beta stocks (HDCC–LDCC).
- Buying high-DCC beta stocks and selling medium-DCC beta stocks (HDCC–MDCC).
- Buying medium-DCC beta stocks and selling low-DCC beta stocks (MDCC–LDCC).

For double sort variables, stocks are sorted by two variables. The first sort variable is size using the firm size median as the breakpoint. Another sort variable is another characteristic like firm value, momentum, Value-at-Risk, conditional Value-at-Risk, illiquidity, CAPM beta, and DCC beta with 30th and 70th percentiles of these characteristics as breakpoints. Therefore, six Size–Value portfolios, six Size–Momentum portfolios, six Size–VaR portfolios, six Size–CVaR portfolios, six Size–Illiquidity portfolios, six Size–CAPM beta portfolios, and six Size–DCC beta portfolios are created. Similar to the single sort analyses, based on the cross-section of stock returns and their firm characteristics (HA1 to HA7) appropriate trading strategies are created as follows:

3.5.4.9. Strategies Based on the Combination of Size and Value (I)

Long strategies (I1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SH (SM/ SL) portfolios should have higher returns than buying stocks in the BH (BM/ BL) portfolios, respectively.

Long strategies (I2): Buying higher-value portfolios should have higher returns than buying lower-value portfolios:

- In the small-size group, buying stocks in the SH portfolio should have a higher return than buying stocks in the SM portfolio, and buying stocks in the SM portfolio should have a higher return than buying stocks in the SL portfolio.
- In the big-size group, buying stocks in the BH portfolio should have a higher return than buying stocks in the BM portfolio, and buying stocks in the BM portfolio should have a higher return than buying stocks in the BL portfolio.

Arbitrage strategies (I3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SH portfolio and sell the BH portfolio (SH–BH).
- Buy the SM portfolio and sell the BM portfolio (SM–BM).
- Buy the SL portfolio and sell the BL portfolio (SL–BL).

Arbitrage strategies (I4): Long higher-value portfolios and short smaller-value portfolios should have positive returns:

- Buy the SH portfolio and sell the SL portfolio (SH–SL).
- Buy the SH portfolio and sell the SM portfolio (SH–SM).

- Buy the SM portfolio and sell the SL portfolio (SM–SL).
- Buy the BH portfolio and sell the BL portfolio (BH–BL).
- Buy the BH portfolio and sell the BM portfolio (BH–BM).
- Buy the BM portfolio and sell the BL portfolio (BM–BL).

3.5.4.10. Strategies Based on the Combination of Size and Momentum (J)

Long strategies (J1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SU (SN/ SD) portfolios should have higher returns than buying stocks in the BU (BD/ BD) portfolios, respectively.

Long strategies (J2): Buying higher-momentum portfolios should have higher returns than buying lower-momentum portfolios:

- In the small-size group, buying stocks in the SU portfolio should have a higher return than buying stocks in the SN portfolio, and buying stocks in the SN portfolio should have a higher return than buying stocks in the SD portfolio.
- In the big-size group, buying stocks in the BU portfolio should have a higher return than buying stocks in the BN portfolio, and buying stocks in the BN portfolio should have a higher return than buying stocks in the BD portfolio.

Arbitrage strategies (J3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SU portfolio and sell the BU portfolio (SU–BU).
- Buy the SN portfolio and sell the BN portfolio (SN–BN).
- Buy the SD portfolio and sell the BD portfolio (SD–BD).

Arbitrage strategies (J4): Long higher-momentum portfolios and short smaller-momentum portfolios should have positive returns:

- Buy the SU portfolio and sell the SD portfolio (SU–SD)
- Buy the SU portfolio and sell the SN portfolio (SU–SN)
- Buy the SN portfolio and sell the SD portfolio (SN–SD)
- Buy the BU portfolio and sell the BD portfolio (BU–BD)
- Buy the BU portfolio and sell the BN portfolio (BU–BN)
- Buy the BN portfolio and sell the BD portfolio (BN–BD)

3.5.4.11. Strategies Based on the Combination of Size and VaR (K)

Long strategies (K1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SHVaR (SMVaR/ SLVaR) portfolios should have higher returns than buying stocks in the BHVaR (BMVaR/ BLVaR) portfolios, respectively.

Long strategies (K2): Buying higher-VaR portfolios should have higher returns than buying lower-VaR portfolios:

- In the small-size group, buying stocks in the SHVaR portfolio should have a higher return than buying stocks in the SMVaR portfolio, and buying stocks in the SMVaR portfolio should have a higher return than buying stocks in the SLVaR portfolio.
- In the big-size group, buying stocks in the BHVaR portfolio should have a higher return than buying stocks in the BMVaR portfolio, and buying stocks in the BMVaR portfolio should have a higher return than buying stocks in the BLVaR portfolio.

Arbitrage strategies (K3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SHVaR portfolio and sell the BHVaR portfolio (SHVaR–BHVaR)
- Buy the SMVaR portfolio and sell the BMVaR portfolio (SMVaR–BMVaR)
- Buy the SLVaR portfolio and sell the BLVaR portfolio (SLVaR–BLVaR)

Arbitrage strategies (K4): Long higher-VaR portfolios and short smaller-VaR portfolios should have positive returns:

- Buy the SHVaR portfolio and sell the SLVaR portfolio (SHVaR–SLVaR)
- Buy the SHVaR portfolio and sell the SMVaR portfolio (SHVaR–SMVaR)
- Buy the SMVaR portfolio and sell the SLVaR portfolio (SMVaR–SLVaR)
- Buy the BHVaR portfolio and sell the BLVaR portfolio (BHVaR–BLVaR)
- Buy the BHVaR portfolio and sell the BMVaR portfolio (BHVaR–BMVaR)
- Buy the BMVaR portfolio and sell the BLVaR portfolio (BMVaR–BLVaR)

3.5.4.12. Strategies Based on the Combination of Size and CVaR (L)

Long strategies (L1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SHCVaR (SMCVaR/ SLCVaR) portfolios should have higher returns than buying stocks in the BHCVaR (BMCVaR/ BLCVaR) portfolios, respectively.

Long strategies (L2): Buying lower-CVaR portfolios should have higher returns than buying higher-CVaR portfolios:

- In the small-size group, buying stocks in the SLCVaR portfolio should have a higher return than buying stocks in the SMCVaR portfolio, and buying stocks in the SMCVaR portfolio should have a higher return than buying stocks in the SHCVaR portfolio.

- In the big-size group, buying stocks in the BLCVaR portfolio should have a higher return than buying stocks in the BMCVaR portfolio, and buying stocks in the BMCVaR portfolio should have a higher return than buying stocks in the BHCVaR portfolio.

Arbitrage strategies (L3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SHCVaR portfolio and sell the BHCVaR portfolio (SHCVaR–BHCVaR)
- Buy the SMCVaR portfolio and sell the BMCVaR portfolio (SMCVaR–BMCVaR)
- Buy the SLCVaR portfolio and sell the BLCVaR portfolio (SLCVaR–BLCVaR)

Arbitrage strategies (L4): Long lower-CVaR portfolios and short higher-CVaR portfolios should have positive returns:

- Buy the SLCVaR portfolio and sell the SHCVaR portfolio (SLCVaR–SHCVaR)
- Buy the SMCVaR portfolio and sell the SHCVaR portfolio (SMCVaR–SHCVaR)
- Buy the SLCVaR portfolio and sell the SMCVaR portfolio (SLCVaR–SMCVaR)
- Buy the BLCVaR portfolio and sell the BHCVaR portfolio (BLCVaR–BHCVaR)
- Buy the BMCVaR portfolio and sell the BHCVaR portfolio (BMCVaR–BHCVaR)
- Buy the BLCVaR portfolio and sell the BMCVaR portfolio (BLCVaR–BMCVaR)

3.5.4.13. Strategies Based on the Combination of Size and Illiquidity (M)

Long strategies (M1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SHIlliq (SMIlliq/ SLIlliq) portfolios should have higher returns than buying stocks in the BHIlliq (BMIlliq/ BLIlliq) portfolios, respectively.

Long strategies (M2): Buying higher-illiquid portfolios should have higher returns than buying lower-illiquid portfolios:

- In the small-size group, buying stocks in the SHIlliq portfolio should have a higher return than buying stocks in the SMIlliq portfolio, and buying stocks in the SMIlliq portfolio should have a higher return than buying stocks in the SLIlliq portfolio.
- In the big-size group, buying stocks in the BHIlliq portfolio should have a higher return than buying stocks in the BMIlliq portfolio, and buying stocks in the BMIlliq portfolio should have a higher return than buying stocks in the BLIlliq portfolio.

Arbitrage strategies (M3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SHIlliq portfolio and sell the BHIlliq portfolio (SHIlliq–BHIlliq)
- Buy the SMIlliq portfolio and sell the BMIlliq portfolio (SMIlliq–BMIlliq)
- Buy the SLIlliq portfolio and sell the BLIlliq portfolio (SLIlliq–BLIlliq)

Arbitrage strategies (M4): Long higher-illiquid portfolios and short lower-illiquid portfolios should have positive returns:

- Buy the SHIlliq portfolio and sell the SLIlliq portfolio (SHIlliq–SLIlliq)
- Buy the SHIlliq portfolio and sell the SMIlliq portfolio (SHIlliq–SMIlliq)
- Buy the SMIlliq portfolio and sell the SLIlliq portfolio (SMIlliq–SLIlliq)
- Buy the BHIlliq portfolio and sell the BLIlliq portfolio (BHIlliq–BLIlliq)
- Buy the BHIlliq portfolio and sell the BMIlliq portfolio (BHIlliq–BMIlliq)
- Buy the BMIlliq portfolio and sell the BLIlliq portfolio (BMIlliq–BLIlliq)

3.5.4.14. Strategies Based on the Combination of Size and CAPM Beta (N)

Long strategies (N1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SHCAPM (SMCAPM/ SLCAPM) portfolios should have higher returns than buying stocks in the BHCAPM (BMCAPM/ BLCAPM) portfolios, respectively.

Long strategies (N2): Buying higher-CAPM beta portfolios should have higher returns than buying lower-CAPM beta portfolios:

- In the small-size group, buying stocks in the SHCAPM portfolio should have a higher return than buying stocks in the SMCAPM portfolio, and buying stocks in the SMCAPM portfolio should have a higher return than buying stocks in the SLCAPM portfolio.
- In the big-size group, buying stocks in the BHCAPM portfolio should have a higher return than buying stocks in the BMCAPM portfolio, and buying stocks in the BMCAPM portfolio should have a higher return than buying stocks in the BLCAPM portfolio.

Arbitrage strategies (N3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SHCAPM portfolio and sell the BHCAPM portfolio (SHCAPM–BHCAPM)
- Buy the SMCAPM portfolio and sell the BMCAPM portfolio (SMCAPM–BMCAPM)
- Buy the SLCAPM portfolio and sell the BLCAPM portfolio (SLCAPM–BLCAPM)

Arbitrage strategies (N4): Long higher-CAPM beta portfolios and short lower-CAPM beta portfolios should have positive returns:

- Buy the SHCAPM portfolio and sell the SLCAPM portfolio (SHCAPM–SLCAPM)
- Buy the SHCAPM portfolio and sell the SMCAPM portfolio (SHCAPM–SMCAPM)
- Buy the SMCAPM portfolio and sell the SLCAPM portfolio (SMCAPM–SLCAPM)
- Buy the BHCAPM portfolio and sell the BLCAPM portfolio (BHCAPM–BLCAPM)
- Buy the BHCAPM portfolio and sell the BMCAPM portfolio (BHCAPM–BMCAPM)
- Buy the BMCAPM portfolio and sell the BLCAPM portfolio (BMCAPM–BLCAPM)

3.5.4.15. Strategies Based on the Combination of Size and DCC Beta (O)

Long strategies (O1): Buying small-size portfolios should have higher returns than buying big-size portfolios:

- Buying stocks in SHDCC (SMDCC/ SLDCC) portfolios should have higher returns than buying stocks in the BHDCC (BMDCC/ BLDCC) portfolios, respectively.

Long strategies (O2): Buying higher-DCC beta portfolios should have higher returns than buying lower-DCC beta portfolios:

- In the small-size group, buying stocks in the SHDCC portfolio should have a higher return than buying stocks in the SMDCC portfolio, and buying stocks in the

SMDCC portfolio should have a higher return than buying stocks in the SLDCC portfolio.

- In the big-size group, buying stocks in the BHDCC portfolio should have a higher return than buying stocks in the BMDCC portfolio, and buying stocks in the BMDCC portfolio should have a higher return than buying stocks in the BLDCC portfolio.

Arbitrage strategies (O3): Long smaller-size portfolios and short bigger-size portfolios should have positive returns:

- Buy the SHDCC portfolio and sell the BHDCC portfolio (SHDCC–BHDCC)
- Buy the SMDCC portfolio and sell the BMDCC portfolio (SMDCC–BMDCC)
- Buy the SLDCC portfolio and sell the BLDCC portfolio (SLDCC–BLDCC)

Arbitrage strategies (O4): Long higher-DCC beta portfolios and short lower-DCC beta portfolios should have positive returns:

- Buy the SHDCC portfolio and sell the SLDCC portfolio (SHDCC–SLDCC)
- Buy the SHDCC portfolio and sell the SMDCC portfolio (SHDCC–SMDCC)
- Buy the SMDCC portfolio and sell the SLDCC portfolio (SMDCC–SLDCC)
- Buy the BHDCC portfolio and sell the BLDCC portfolio (BHDCC–BLDCC)
- Buy the BHDCC portfolio and sell the BMDCC portfolio (BHDCC–BMDCC)
- Buy the BMDCC portfolio and sell the BLDCC portfolio (BMDCC–BLDCC)

3.6. Conclusion

This chapter represents the conceptual framework and methodologies for this thesis. This includes three analyses: firm characteristics, common risk factors, and stock selection for trading strategies. Variables are defined for both stock and portfolio levels. For the analysis of firm characteristics and stock returns, different methods are introduced to test hypotheses from the literature including Fama–MacBeth regression, between estimator, pool OLS estimator, fixed effects, and random effects. In addition, this chapter presents different tests: multicollinearity, normal distribution, serial correlation, and cross-sectional dependence. Furthermore, robustness using Newey West and double clustering is applied to make the statistical inferences more efficient and effective. For common risk factors, different factor models are tested to select the best risk model for the HSX. For stock selection, the chapter recommends different strategies based on firm characteristics and common risk factor models. Parametric and nonparametric methods are introduced to test these strategies to find out what stocks should buy and what stocks should sell. The next chapter gives an overview of the Vietnamese stock market and descriptive statistics of the sample data containing stock returns, firm characteristics, portfolio returns, and risk factors.

Chapter 4: Vietnam Stock Market and Descriptive Statistics of the Data

4.1. Introduction

This chapter provides an overview of the market and descriptive statistics for advanced analyses in the following chapters. First, this chapter introduces the structure of the Vietnam stock market and trading stocks in stock exchanges. Then the method to select stocks is presented to form the sample on the Ho Chi Minh Stock Exchange (HSX). Following, the portfolios and common risks are built based on the sample. Next, descriptive statistics of the sample are analysed to understand the characteristics of the sample data, the portfolios, and the common risks for further analysis in the following chapters. The formulas of these variables are shown in the previous chapter.

4.2. The Organisation of the Vietnam Stock Market

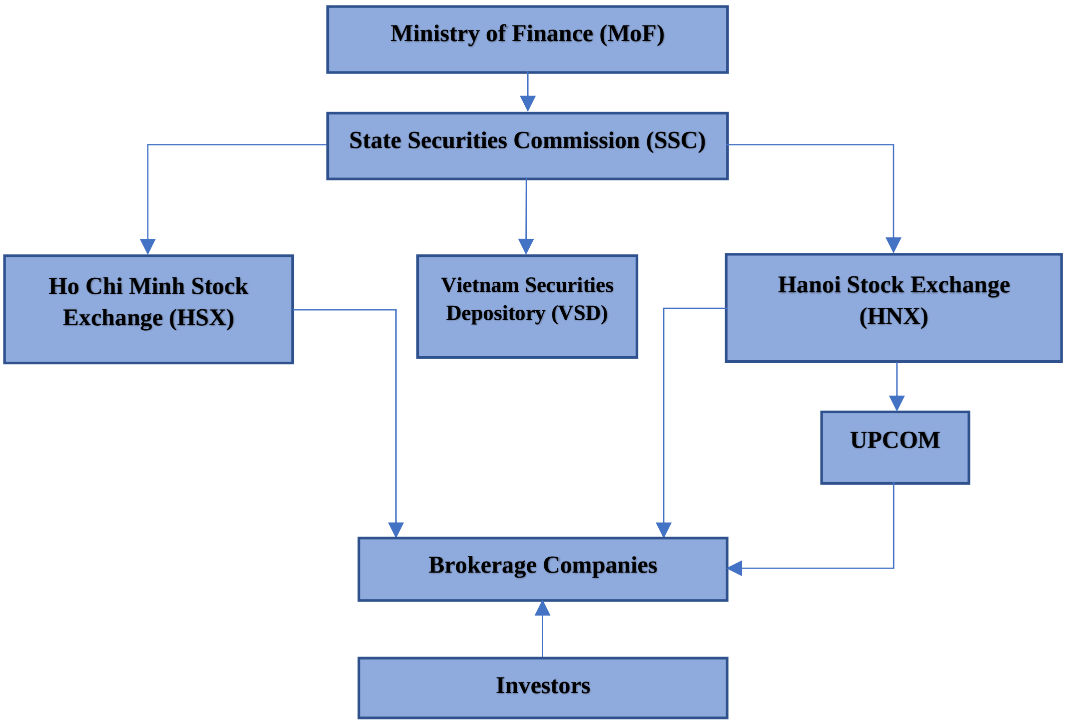


Figure 4.1: Organisation of Vietnam Stock Market

Source: Synthesis from websites of MoF, SSC, HSX, and HNX, accessed 8 March 2021.

4.2.1. The Ministry of Finance (MoF)

The MoF is a government agency that has the function of implementing the State management in finance (including the State budget, tax, fees, and other revenues of the State budget, national reserve, State financial funds, financial investment, corporate finance, and financial services); customs; accounting; independent auditing; insurance; prices; securities; conducting the ownership rights to the state's investment capital in enterprises according to regulations of the Law.

4.2.2. The State Securities Commission (SSC)

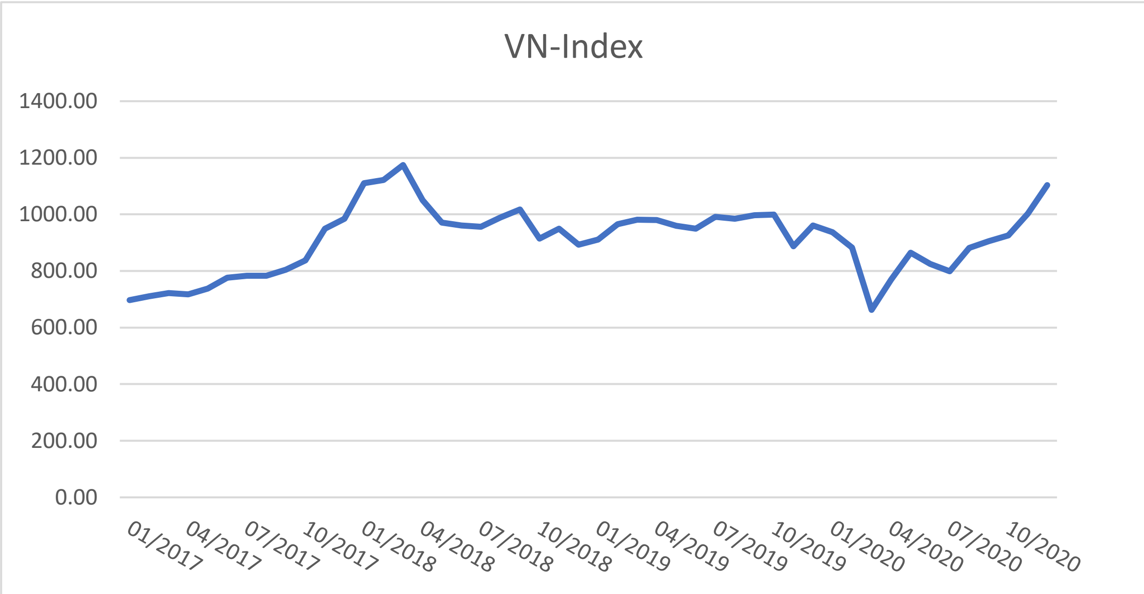
At the end of 1996, The SSC was established with the mission of organising and regulating the operation of securities. The establishment of this securities regulator before the actual function of the securities market is consistent with the general directives of building and developing the securities market in Vietnam. This step determined the birth of the securities market three years later. The SSC regulates securities and the stock market. Furthermore, the SSC directs the regulation and supervision of activities in this field. They also manage the securities services following applicable laws.

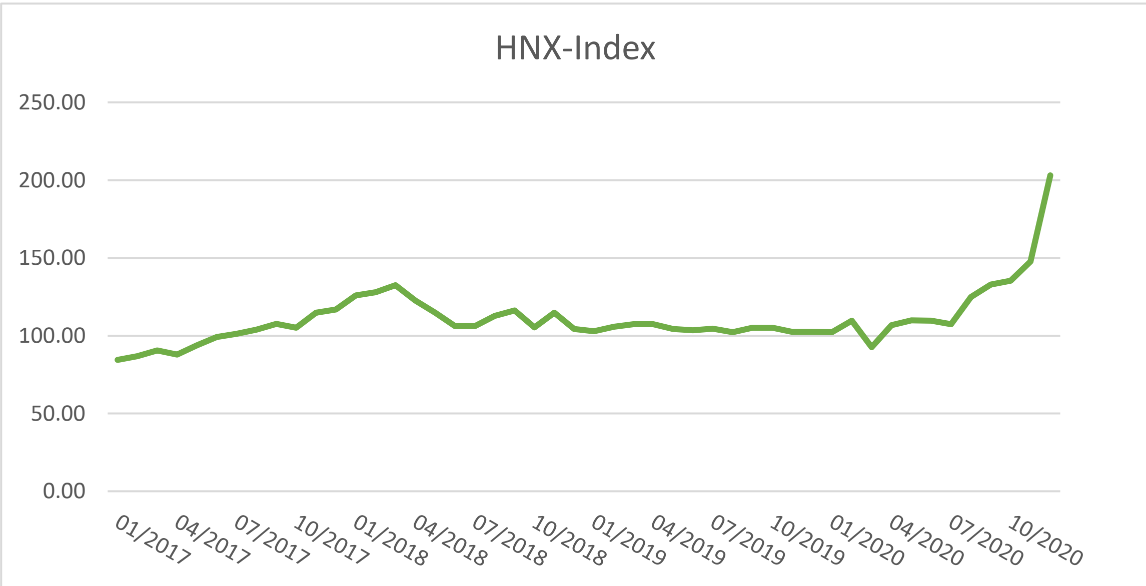
4.2.3. Vietnam Securities Depository (VSD)

The VSD was established in 2005, and this is the agent providing supporting services including securities registration, securities depository, corporate actions, e-voting, allocation of securities codes, fund services, allocation of trading codes for foreign investors, securities borrowing and lending, clearing, and settlement of securities transactions to the whole securities market.

4.2.4. Stock Exchanges

There are two stock exchanges in Vietnam: the Ho Chi Minh Stock Exchange (HSX) and the Hanoi Stock Exchange (HNX). The Vietnamese stock market was established in 2000, with the establishment of Ho Chi Minh City Securities Trading Center, and it was renamed the Ho Chi Minh Stock Exchange (HSX) in 2007. The Hanoi Securities Trading Center was established in 2005, and was renamed the Hanoi Stock Exchange (HNX) in 2009. In June 2009, the Unlisted Public Company Market (UPCOM) was launched, and it is under the supervision of the HNX. Figure 4.2 below shows monthly indices of the VN index, HNX index, and UPCOM index from January 2017 to December 2020.





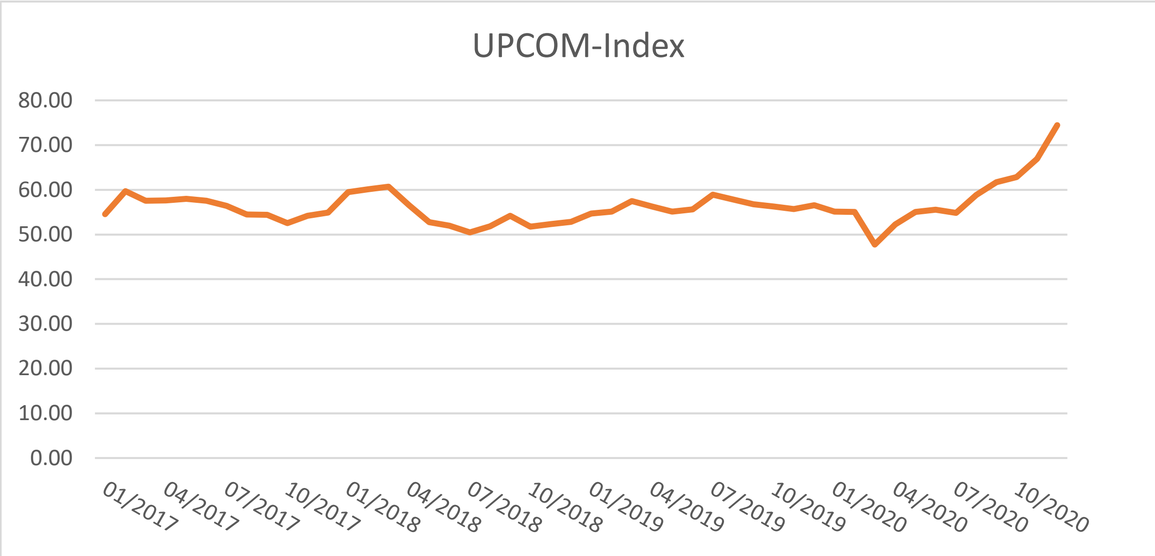


Figure 4.2: Monthly Indices (January 2017 – December 2020)

Source: data collected on SSC website, accessed 8 March 2021.

The HSX is the biggest stock exchange in Vietnam. According to the statistics from the website of the State Securities Commission of Vietnam (SSC), at the end of 2020, the market capitalisation of the HSX was approximately 19 times bigger than that of the Hanoi Stock Exchange (HNX), at approximately 4,080,757 billion VND and 212,320 billion VND, respectively. Simultaneously, the market capitalisation of the HSX was approximately four times higher than that of the UPCOM which was approximately 1,000,696 billion VND. The number of listing companies in the HSX, HNX, and UPCOM were 378, 367, and 872, respectively at the end of 2020. The graph below shows the monthly indices of the HSX (VN Index), HNX (HNX Index), and UPCOM (UPCOM Index) from January 2017 to December 2020. The maximum values of the VN Index, HNX Index, and UPCOM Index were approximately 1,174; 203; and 74, respectively. In contrast, the minimum values of VN Index, HNX Index, and UPCOM Index were approximately 663; 84; and 47, respectively.

4.2.5. Brokerage Firms

According to information from the SSC website accessed in March 2021, there were 88 active brokerage companies in the Vietnam stock market. The 10 largest brokerage firms in Vietnam in terms of charter capital are Saigon Securities Incorporation (SSI), Mirae Asset Securities (Vietnam) Limited Liability Company (MAS), VPS Securities Joint Stock Company (VPS), Ho Chi Minh City Securities Corporation (HSC), Vndirect Securities Corporation (VNDIRECT), Agribank Securities Corporation (AGRISECO), Saigon – Hanoi Securities Joint Stock Company (SHS), KIS Viet Nam Securities Corporation (KIS), KB Securities Joint Stock Company (KBSV), and Viet Capital Securities Joint Stock Company (VCSC). Table 4.1 shows the charter capital of the 10 brokerage firms in Vietnam.

Table 4.1: The charter capital of the top 10 brokerage firms

Brokerage Firms	Charter Capital (VND Billion)
SSI	6,029
MAS	4,300
VPS	3,500
HSC	3,059
VNDIRECT	2,204
AGRISECO	2,120
SHS	2,073
KIS	1,897
KBSV	1,675
VCSC	1,630

Source: SSC website, accessed 8 March 2021

4.2.6. Investors

According to the website of the VSD, at the end of 2020, there were approximately 2.7 million trading accounts registered at the VSD. The accounts of domestic investors account for 98.7 per cent, while the accounts of foreign investors were only 1.3 per cent. Individual investors accounted for approximately 99.5 per cent while institutional investors were only 0.5 per cent.

Figure 4.3 below shows the number of domestic and foreign investors that are divided into individual and institutional categories.

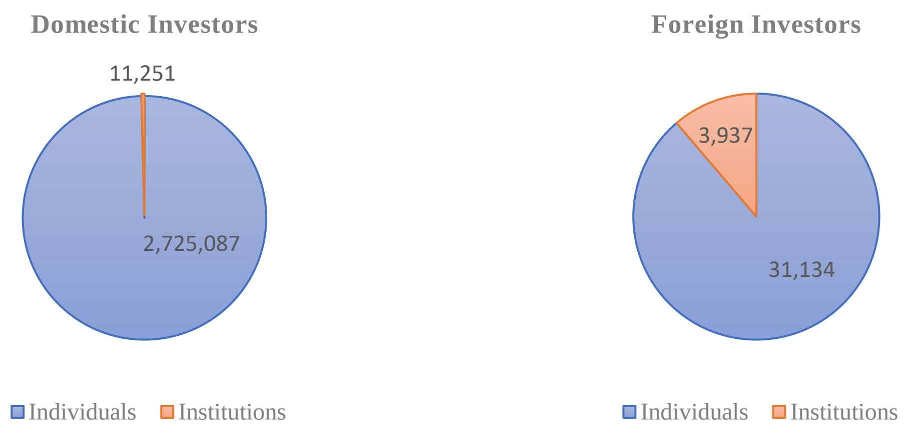


Figure 4.3: Investors in Vietnam Stock Market at the End of 2020

Source: VSD website, accessed 8 March 2021.

4.3. Securities Trading

In the Vietnam stock market, trading hours last from Monday to Friday and exclude public holidays. There are two trading sessions: from 9:00 to 11:30 and from 13:00 to 15:00. The intermission of each trading day is from 11:30 to 13:00.

Three trading methods are applied in Vietnam: periodical order matching, continuous order matching, and put-through. Periodical order matching is the method that compares buy and sell orders at specified times of a trading day. The matching price is the price where the greatest matching volume can be executed based on the bids and asks at that time. Investors are not allowed to cancel orders in periodic order matching sessions. Continuous order matching is the method that compares buy and sell orders immediately when they are put into the trading system. The executed price is based on the price of counter orders waiting on the order book. In continuous order matching sessions, investors are allowed to cancel unmatched orders. Put-through is another method that allows buyers and sellers to negotiate the price and volume by themselves. After the negotiation, buyers and sellers notify the brokerage firms to record the results into the transaction system.

Investors use different orders to buy or sell stocks in the HSX, HNX, and UPCOM. The matching principles depend on two factors: price priority and time priority. First, buying orders at a higher price will have a higher priority. However, selling orders at a lower price will have a higher priority. Second, orders entered into the trading system earlier will take precedence. If a transaction is successful, the settlement of stocks is executed within two business days which means stock purchased on date T can be sold on T+3. The price and volume are controlled in the Vietnamese stock market. The details of trading sessions, trading methods, and orders in each market are represented below.

4.3.1. Trading on the HSX

Table 4.2: Trading on the HSX

Trading Hours	**Trading Methods**	**Orders**
9:00 – 9:15	Periodic order matching	ATO, LO Orders cannot be cancelled
9:15 – 11:30	Continuous order matching	LO, MP Orders can be cancelled
11:30 – 13:00	Intermission	
13:00 – 14:30	Continuous order matching	LO, MP Orders can be cancelled
14:30 – 14:45	Periodic order matching	ATC, LO Orders cannot be cancelled
9:00 – 11:30 & 13:00 – 15:00	Put-through	Put-through order

Notes:

LO (limit order): buying or selling at a specific price in the price range and validates until the end of a trading day or until the order is cancelled.

ATO (at the open)/ ATC (at the close): the order at opening price or closing price, which is not given a specific price, is called ATO/ ATC. ATO/ ATC orders have a higher priority to match than limit orders. At the end of the effective session, unmatched ATO/ ATC orders or unmatched volume of partially matched ATO / ATC orders will be cancelled automatically.

MP (market price order): orders to match the best counter bids/ asks available in the system at the time of input and will match forward to the next best prices available. If there is no counter LO order at the time of input of the MP order, the MP order will automatically be cancelled.

Source: SSI and HSC websites, accessed 8 March 2021.

Table 4.2 shows trading hours, trading methods, and orders in the HSX. Prices of stocks on the HSX are controlled between negative 7 per cent and positive 7 per cent compared to the reference (the closing price of the latest trading day). For newly listed stocks or re-traded stocks after a 25-day stopped trading, the price range on the first trading day is between negative 20 per cent and positive 20 per cent.

The trading unit of order matching is a multiple of 100. The maximum trading volume per order is 500,000 shares. The trading volume of put-through transactions is from 20,000 shares. There is no regulation on the trading unit for a put-through transaction.

4.3.2. Trading on the HNX

Table 4.3: Trading on the HNX

Trading Hours	**Trading Methods**	**Orders**
9:00 – 11:30	Continuous order matching	LO, MTL, MOK, MAK Orders can be cancelled/ amended
11:30 – 13:00	Intermission	
13:00 – 14:30	Continuous order matching	LO, MTL, MOK, MAK Orders can be cancelled/ amended
14:30 – 14:45	Periodic order matching	ATC, LO Orders cannot be cancelled/ amended
14:45 – 15:00	Post-session order matching	PLO Orders cannot be cancelled/ amended
9:00 – 11:30 & 13:00 – 15:00	Put-through	Put-through order

Notes:

LO (limit order): buying or selling at a specific price or a better price and validates until the end of the trading day or until the order is cancelled.

MTL (market to limit): this is a market price order (MP). However, if there are no more counter bids/ asks, the remaining unmatched volume of MTL will be changed into LO automatically

MOK (match or kill): this is a market price order (MP). However, the order must be executed in its entirety at the time of input; otherwise, the entire order will be cancelled.

MAK (match and kill): this is a market price order (MP). However, the order can be executed partially or entirely, and the remaining unmatched order will be cancelled.

ATC (at the close): the order is at the closing price and is not given a specific price. ATC orders have a higher priority to match than LO. At the end of the effective session, unmatched ATC orders or unmatched volume of partially matched ATC orders will be cancelled automatically.

Trading Hours	Trading Methods	Orders
PLO (post limit order): the buy or sell orders are used in the post-session session at the closing price. PLO is matched right after a counter order appears and is automatically canceled after a post-session transaction has ended. If the execution price from continuous order matching and the closing session cannot be determined, PLO orders cannot be placed.		

Source: SSI and HSC websites, accessed 8 March 2021.

Table 4.3 shows trading hours, trading methods, and orders in the HNX. Prices of stocks on the HNX are controlled between negative 10 per cent and positive 10 per cent compared to the reference (the closing price of the latest trading day). For newly listed stocks or re-traded stocks after a 25-day stopped trading, the price range on the first trading day is between negative 30 per cent and positive 30 per cent.

The trading unit of order matching is a multiple of 100. The trading volume of put-through transactions is from 5,000 shares. There is no regulation on the trading unit for a put-through transaction.

4.3.3. Trading on the UPCOM

Table 4.4: Trading on UPCOM

Trading Hours	Trading Methods	Orders
9:00 – 11:30	Continuous order matching	LO Orders can be cancelled/amended
11:30 – 13:00	Intermission	
13:00 – 15:00	Continuous order matching	LO Orders can be cancelled/amended
9:00 – 11:30 & 13:00 – 15:00	Put-through	Put-through order
Notes: *LO (limit order): buying or selling at a specific price or a better price and validates until the end of the trading day or until the order is cancelled.*		

Source: SSI and HSC websites, accessed 8 March 2021.

Table 4.4 shows trading hours, trading methods, and orders in the UPCOM. Prices of stocks on the UPCOM are controlled between negative 15 per cent and positive 15 per cent compared to the reference price (the weighted average of even lot trading prices calculated from the continuous order matching method of the latest trading day). For newly listed stocks or re-traded stocks after a 25-day stopped trading, the price range on the first trading day is between negative 40 per cent and positive 40 per cent.

The trading unit of order matching is a multiple of 100. There is no regulation on the trading unit for a put-through transaction.

4.4. Sample Data

4.4.1. Stock Returns and Firm Characteristics

The stock returns and firm characteristics include the 100 largest non-financial stocks (see Appendix) which were traded on the HSX and were measured from January 2011 to December 2019 (108 months). First, financial companies including banks, securities, insurance, and real estate investment are excluded from the sample because these stocks have higher leverage and different nature of business compared to non-financial stocks (Fama & French, 1992; Hanauer & Lauterbach, 2019; Vo, 2016). Second, the period 2011–2019 is selected to remove the negative effect of the global financial crisis in 2007–2008. The panel data formed by the sample has 10,800 observations for each variable if there have none of missing values.

A normal distribution is symmetrical; however, some variables are skewed by nature. For example, market capitalisation and book-to-market ratio are always positive; therefore, they are right-skewed. Second, the normal distribution is a continuous function, but many accounting and financial data are not available in real time. Stock markets do not work 24 hours a day and seven days a week. They are often off on weekends and public holidays. Furthermore, accounting data are not public every day; however, they are reported quarterly. Therefore, the intermissions in trading and infrequent reporting cause the accounting and financial data to be not continuous. Moreover, the cross-sectional data used in accounting and finance are subject to extreme observations which are severe non-normality (Bali et al., 2016; Brownen-Trinh, 2019; Templeton & Burney, 2017). This issue may cause biases in regression studies. To reduce the negative effects of the non-normality problem, natural log transformations, scaling and winsorisation are applied to the sample data (Bali et al., 2016; Bauer et al., 2012; Cong & Romero, 2013; Hanauer & Lauterbach, 2019).

Nine variables are computed in the sample data: the monthly return, CAPM beta, DCC beta, Size, Value, Momentum, VaR, CVaR, and Illiquidity. The logarithmic returns are used to reduce the negative effect of thin trading (Fowler et al., 1979). The DCC betas are dynamic betas estimated by using the DCC multivariate GARCH model for excess monthly returns of stocks and market returns (Engle, 2002). This model is expected to bring better results in beta estimations because the dynamic feature of the model allows the DCC betas to vary each month in the estimation period. Although the CAPM betas fluctuate each month because of monthly rolling regression, they are unchanged within an estimation window (Bali et al., 2017). Size and value variables are the natural logarithm of market capitalisation and book-to-market ratio, respectively (Fama & French, 1992). The illiquidity is the logarithm of the ratio of the total absolute value of daily returns divided by the daily volume traded in billion dongs, average over trading days in each month (Amihud, 2002). Logarithmic transformations are applied to firm size, firm value, and illiquidity to make them less skewed (Bali et al., 2016). Also, firm size is scaled and measured in thousand billion dongs (Vietnamese currency) to make it more symmetric. Momentum is the past 11-month cumulative returns (Bali et al., 2016; Jegadeesh & Titman, 1993). Value-at-Risk (VaR) is measured by negative one times the 5 per cent quantile of the distribution of monthly stock returns to represent the downside risk (Bali & Cakici, 2004; Bali et al., 2007). The conditional VaR (CVaR) is the average of the loss that falls beyond the VaR (Abad et al., 2014; Nguyen et al., 2019; Unbreen & Sohail, 2020). Similar to the VaR, CVaR is multiplied by negative 1 to measure the downside risk. All variables are winsorised at 0.1th and 99.9th percentiles to reduce the negative effects of outliers for further analyses using regressions (Bali et al., 2016; Hanauer & Lauterbach, 2019).

4.4.2. Portfolio Returns and Risk Factors

Portfolio returns are constructed by the combinations of size and other firm characteristics and are rebalanced monthly: firm size and firm value, firm size and momentum, firm size and VaR, firm size and CVaR, firm size and illiquidity, firm size and CAPM beta, firm size, and DCC beta. The median is the breakpoint for firm size to separate stocks into two groups small and big. Thirtieth and 70th percentiles are the breakpoints for other variables to isolate stocks into three groups high (up), medium (neutral), and low (down). Therefore, each combination will have six portfolios. The portfolio returns are average value-weighted.

The risk factors are the MKT (market risk factor) (Black et al., 1972; Sharpe, 1964), SMB (size factor) and HML (value factor) (Fama & French, 1993; Rashid et al., 2018; Xie & Qu, 2016), UMD (momentum factor) (Carhart, 1997; Fama & French, 2012; Hanauer & Lauterbach, 2019), HVaRL (Value-at-Risk factor) (Aziz & Ansari, 2017; Bali & Cakici, 2004; Chen et al., 2014), LCVaRH (conditional Value-at-Risk factor) (Ling & Cao, 2020; Tokpavi & Vaucher, 2012), HILLIQL (illiquidity factor) (Amihud, 2002; Bali & Cakici, 2004; Marcelo & Quirós, 2006), RMW (profitability factor) and CMA (investment factor) (Fama & French, 2015; Hou et al., 2015). They are constructed in December each year. The excess return of the VN-index represents the market risk portfolio (MKT). Other factors are arbitrage portfolios using the median as the breakpoint for all these factors to separate stocks into high and low groups. Returns of the SMB and HML are the average value-weighted returns of small-size portfolios minus the average value-weighted returns of big-size portfolios, and the average value-weighted returns of high-value portfolios minus the average value-weighted returns of low-value portfolios, respectively. Similarly, returns of the UMD are the average value-weighted returns of high-momentum portfolios minus the average value-weighted returns of low-momentum portfolios. While returns of HVaRL are the average value-weighted returns of high-VaR portfolios minus the average value-weighted returns of low-VaR portfolios, returns of the LCVaRH are the average value-weighted returns of low-CVaR portfolios minus the average value-weighted returns of high-CVaR portfolios. Likewise, returns of the HILLIQL and RMW are the average value-weighted returns of high-illiquidity portfolios minus the average value-weighted returns of low-illiquidity portfolios, and the average value-weighted returns of high-profitability portfolios minus the average value-weighted returns of low-profitability portfolios, respectively. Returns of the CMA are the average value-weighted returns of low-investment portfolios minus the average value-weighted returns of high-investment portfolios.

The risk factors are often formed by double sort variables. The first sort is always firm size and another sort is another firm characteristic (Bali & Cakici, 2004; Carhart, 1997; Fama & French, 1993; 2015). Because the sample stocks in this thesis are limited to 100 stocks over nine years (108 months). Therefore, this thesis reduces the breakpoints and uses a single-sort variable to construct the portfolios for both dependent and independent to increase the power of portfolios and factors by increasing the number of stocks in each portfolio.

To test the factor models, researchers often use 25 portfolios formed by size quintile and value quintile (Bali & Cakici, 2004; Fama & French, 1993; 2015). In contrast, this research uses different combinations between size and other characteristics to test factor models. Each combination includes six portfolios.

4.5. Descriptive Statistics

4.5.1. Stock Returns and Firm Characteristics

Table 4.5: Descriptive Statistics of Monthly Stock Returns and Firm Characteristics

Statistics / Variables	N	Mean	St. Dev.	Skewness	Excess Kurtosis	Min	Max
Monthly Returns	10,800	0.7834	10.9175	1.1535	5.1305	−36.7226	70.9816
CAPM Beta	10,800	0.6881	0.5180	−0.0698	0.0997	−1.1737	2.1226
DCC Beta	10,800	0.6392	0.4135	0.6227	1.0991	−0.3970	2.6406
Firm Size	10,800	−0.3053	1.4880	0.7288	0.6185	−3.3432	5.4627
Firm Value	10,750	−0.0069	0.6107	−0.4046	0.7920	−2.6439	1.7066
Momentum	10,800	9.3646	46.2873	2.1792	9.8892	−76.4314	366.6160
VaR	10,800	13.7112	5.3841	1.0080	1.9638	3.9765	40.3362
CVaR	10,800	17.6130	6.6705	0.8842	1.1762	4.5911	45.5844
Illiquidity	10,781	−2.6611	3.0881	−0.0683	−0.9915	−9.8101	3.9604

Notes: The formulas of these variables are shown in Chapter 3. Descriptive statistics of monthly stock returns and firm characteristics are computed from Jan 2011 to December 2019.

- *VaR and CVaR are multiplied by negative 1 to represent the downside risk.*
- *Firm size is scaled and measured in a thousand billion Vietnamese dongs before taking the logarithm.*

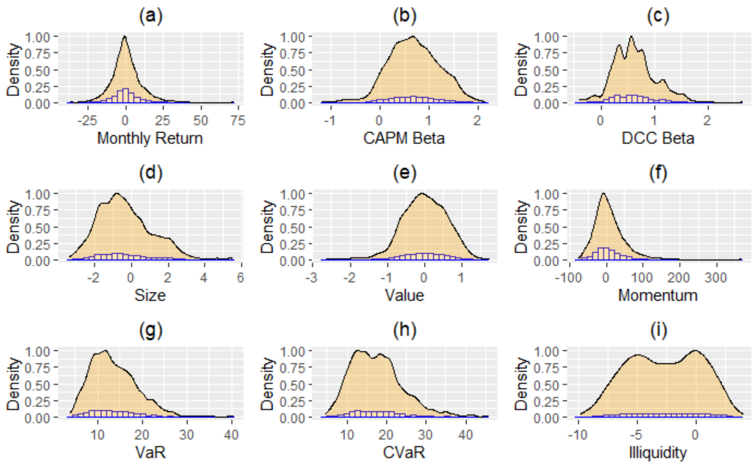


Figure 4.4: Distributions of Monthly Stock Returns and Firm Characteristics

Table 4.5 provides key statistics including mean, standard deviation, skewness, excess kurtosis, minimum, and maximum values of the panel data containing 100 stocks from January 2011 to

December 2019 for the monthly stock returns and their firm characteristics: CAPM beta, DCC beta, firm size, firm value, momentum, Value-at-Risk (VaR), conditional VaR (CVaR), and illiquidity to summarize the variables that are being used for the test of the relation between firm characteristics and stock return on the HSX in Chapter 5. It is important because it provides a brief interpretation of the data where further analyses are performed. Figure 4.4 shows the distributions of these variables.

4.5.1.1. Monthly Stock Returns

The mean of the monthly returns in the sample data is approximately 0.78 per cent. The minimum and maximum returns are nearly -37 per cent and 71 per cent, respectively. The standard deviation of monthly stock returns is about 10.9 per cent. The skewness and excess kurtosis are approximately 1.15 and 5.13, respectively. This shows that the monthly return is right skewed; however, it is not severe because the skewness is around 1 (Hair et al., 2017). The tails of monthly returns are heavier than the normal distribution because of the high excess kurtosis (Hair et al., 2017; Tsay, 2012). The distribution of monthly returns is called leptokurtic (see Figure 4.4a).

4.5.1.2. CAPM Beta and DCC Beta

The mean of CAPM beta is higher than the mean of DCC beta, 0.69 and 0.64, respectively. This shows that the systematic risk of individual stocks in the sample is less than the systematic risk of the market. The minimum and maximum of CAPM beta are approximately -1.17 and 2.12, respectively, while that of DCC beta are nearly -0.4 and 2.6, respectively. The standard deviation of CAPM beta is higher than the DCC beta, 0.52 compared to 0.41, respectively. The CAPM beta is slightly left-skewed because of negative skewness (approximately -0.07), while the DCC beta is slightly right-skewed because of positive skewness (approximately 0.6). Both CAPM beta and DCC beta have thicker tails than the normal distribution because of positive excess kurtosis, approximately 0.1 and 1.1, respectively. The distributions of CAPM beta and DCC beta are called leptokurtic (see Figure 4.4b and c).

4.5.1.3. Firm Size

The mean and standard deviation of the firm size in the panel data are approximately –0.31 and 1.46, respectively. The minimum and maximum sizes are approximately –3.3 and 5.5, respectively. This variable is slightly right-skewed because of positive skewness (approximately 0.73), and it has thicker tails than the normal distribution because of positive excess kurtosis (approximately 0.62). The distribution of the firm size is called leptokurtic (see Figure 4.4d).

4.5.1.4. Firm Value

The mean of the firm value in the panel data is around –0.007, which means the book value of individual stocks is much less than its market value. The minimum and maximum values of this variable are approximately –2.64 and 1.71, respectively. The standard deviation of this variable is nearly 0.61. This variable is slightly left-skewed because of negative skewness (approximately –0.4), and it has thicker tails than the normal distribution because of positive excess kurtosis (approximately 0.79). The distribution of the firm value is called leptokurtic (see Figure 4.4e).

4.5.1.5. Momentum

The mean and standard deviation of momentum are approximately 9.36 and 46.29, respectively. Because of the high standard deviation, the momentum fluctuates in a wide range, from –76.43 to 366.61. The momentum is right skewed because of positive skewness (approximately 2.2), and it has heavy tails compared to the normal distribution because of high positive excess kurtosis (approximately 9.9). The distribution of the momentum variable is called leptokurtic (see Figure 4.4f).

4.5.1.6. Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR)

The mean of CVaR is higher than the mean of VaR, approximately 17.6 and 13.7, respectively. The minimum and maximum of CVaR are approximately 4.6 and 45.6, respectively, while that of VaR are nearly 4 and 40.3. The standard deviation of CVaR is higher than VaR, 6.7 compared to 5.4, respectively. Both VaR and CVaR are right skewed because of positive skewness, approximately 1 and 0.9, respectively. Also, they have thicker tails than the normal distribution because of positive excess kurtosis, approximately 1.96 for VaR and 1.18 for CVaR. The distribution of CAPM beta and DCC beta is called leptokurtic (see Figure 4.4g and h).

4.5.1.7. Illiquidity

The mean of illiquidity is nearly –2.66. The minimum and maximum values are approximately –9.8 and 3.9, respectively. The standard deviation of this variable is nearly 3.08. The skewness and excess kurtosis are approximately –0.07 and –0.99, respectively. This shows that illiquidity is left skewed, and it has thinner tails than the normal distribution. The distribution of the VaR is called platykurtic (see Figure 4.4i).

4.5.2. Portfolio Returns and Risk Factors

Variables estimated using historical data can cause "errors-in-variables", and regressions using these variables lead to biases (Bhandari, 1988; Fama & French, 1992; Fama & MacBeth, 1973). Testing asset pricing models using portfolios can reduce this issue (Ang et al., 2020; Black et al., 1972; Fama & French, 1993; Gibbons et al., 1989; Jagannathan & Wang, 2002). Therefore, this thesis creates 42 portfolios and nine risk factors to test the relationship between the portfolio returns and risk factors (Chapter 6). Furthermore, based on the factor models and the relationship between stock return and their firm characteristics (Chapter 5), the thesis provides efficient strategies for investors in the HSX (Chapter 7).

Tables 4.6 and 4.7 below provide key statistics including mean, standard deviation, skewness, excess kurtosis, minimum, and maximum values of the monthly returns of the risk factors and portfolio returns, respectively from January 2011 to December 2019 to summarise the variables that are being used for the test of factor models in Chapter 6. It is important because it provides a brief interpretation of the data where further analyses are performed. Figures 4.5 to 4.12 below show the distributions of monthly returns of all risk factors and different portfolio returns.

4.5.2.1. Risk Factors

Table 4.6: Descriptive Statistics of Monthly Returns of Risk Factor

Statistics / Risk Factors	N	Mean	St. Dev.	Skewness	Excess Kurtosis	Min	Max
MKT	108	0.1315	5.2833	−0.0606	0.3943	−13.2366	15.1274
SMB	108	0.6391	5.0738	0.3813	0.5329	−13.5801	16.7258
HML	108	0.3142	4.7834	−0.0581	−0.2920	−12.1458	11.1415
UMD	108	−0.6840	5.2888	−0.0714	1.0558	−16.9065	16.3281
HVaRL	108	−0.0147	4.8770	−0.2621	0.0947	−14.2152	11.9562
LCVaRH	108	0.1938	4.7141	0.1376	−0.0939	−12.6400	12.3483
HILLIQL	108	0.2997	4.9306	−0.2756	0.6245	−16.4371	13.9229
RMW	108	0.4667	5.0913	0.2976	0.2634	−12.2114	15.6773
CMA	108	−0.0734	4.0627	0.0641	0.1471	−10.5789	11.1277

Notes: MKT is the excess return of the VN index. Other factors are arbitrage portfolios constructed using single sorting from January 2011 to December 2019. The details of portfolio constructions are shown in Chapter 3. Descriptive statistics of monthly returns of risk factors are calculated from January 2011 to December 2019.

Table 4.6 shows that while the average monthly returns of UMD, HVaRL, and CMA factors are negative, other risk factors have positive returns. The average monthly returns of SMB, HML, LCVaRH, HILLIQL, and RMW are higher than the average returns of the MKT factor. Furthermore, the standard deviation of the MKT is higher than these factors. Therefore, combining MKT with SMB, HML, LCVaRH, and HILLIQL is expected to improve the effects of factor models in explaining stock returns on the HSX. The detailed tests are conducted in Chapter 6.

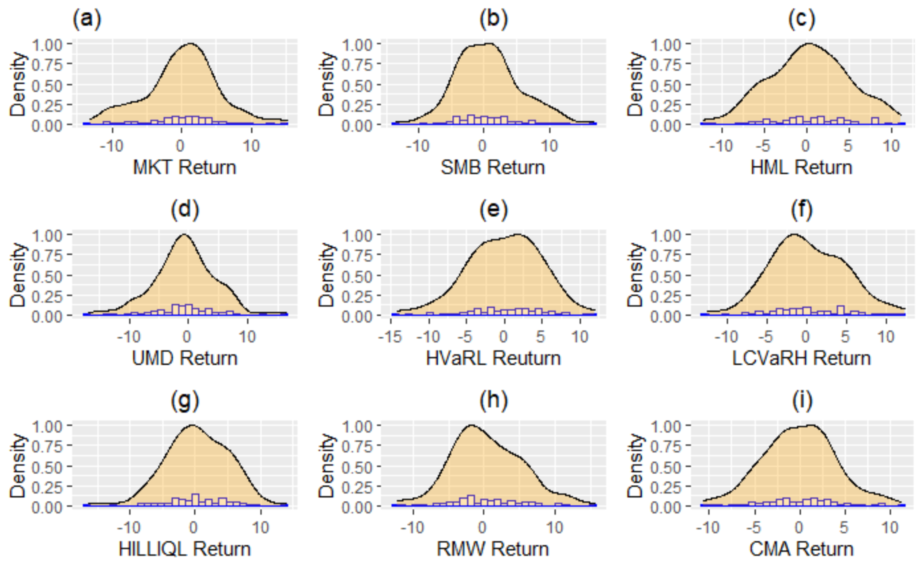


Figure 4.5: Distributions of Monthly Returns of Risk Factors

Figure 4.5 shows distributions of monthly returns of risk factors. Figure 4.5 shows that the monthly returns of MKT, HML, UMD, HVaRL, and HILLIQL are left skewed because of negative skewnesses. In contrast, SMB, LCVaRH, RMW, and CMA are right skewed because of positive skewness. Only the HML and LCVaRH have thinner tails than the normal distribution because their excess kurtosis values are negative. Other factors have heavier tails than the normal distribution because of positive kurtosis values. The distributions of the HML and LCVaRH are called platykurtic, while the distributions of other factors are called leptokurtic.

4.5.2.2. Size–Value Portfolios

All six portfolios formed by firm size and firm value have positive average excess returns (see Panel A, Table 4.7). While the SL portfolio has the lowest monthly return (approximately 0.44%), the SM portfolio has the highest monthly return (approximately 1.61%). The standard deviations of excess monthly returns of Size–Value portfolios fluctuate from 5.4 per cent to 8.2 per cent. All Size–Value portfolios are right skewed and they have heavier tails than the normal distribution because of positive both skewness and excess kurtosis. The distributions of all six Size–Value portfolios are leptokurtic and are shown in Figure 4.6.

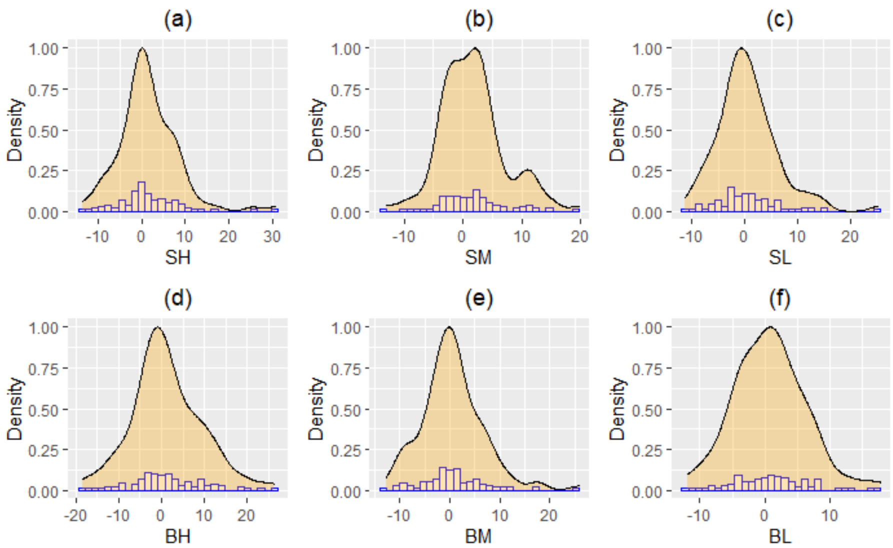


Figure 4.6: Distributions of Monthly Excess Returns of Size–Value Portfolios

Table 4.7: Descriptive Statistics of Monthly Excess Returns of Portfolios

Statistics / Portfolios	**N**	**Mean**	**St. Dev.**	**Skewness**	**Excess Kurtosis**	**Min**	**Max**
Panel A: Size–Value Portfolios							
SH	108	1.4425	6.7224	1.0410	3.4522	−13.5529	30.5041
SM	108	1.6100	5.4238	0.5667	0.9158	−13.0691	19.5891
SL	108	0.4400	5.7336	0.9901	2.5363	−11.3291	25.1513
BH	108	1.2391	8.2231	0.3765	0.5245	−18.4892	26.3487
BM	108	0.5192	6.2308	0.8118	2.0718	−12.7589	25.8138
BL	108	0.7466	5.5374	0.3456	0.4549	−11.8447	17.8603

Statistics / Portfolios	N	Mean	St. Dev.	Skewness	Excess Kurtosis	Min	Max
Panel B: Size–Momentum Portfolios							
SU	108	1.9408	5.7249	0.2957	−0.4387	−10.3056	15.9644
SN	108	1.3658	4.4966	0.0871	0.1613	−9.8190	14.0187
SD	108	0.7922	7.8132	1.2075	3.4189	−18.3069	35.5868
BU	108	0.7663	5.4208	0.3491	0.3375	−12.1500	16.1509
BN	108	0.5825	5.9806	0.4335	0.4572	−12.3261	18.0796
BD	108	−0.2443	7.5727	0.5880	2.0402	−21.0426	29.1121
Panel C: Size–VaR Portfolios							
SHVaR	108	2.3824	7.9163	0.7927	1.7983	−15.6465	33.4497
SMVaR	108	0.6170	4.5189	0.0288	0.6230	−13.0804	14.0388
SLVaR	108	0.9291	4.0156	0.1819	−0.1632	−7.4695	11.4873
BHVaR	108	0.0277	7.4221	0.7381	1.1336	−15.1484	26.2833
BMVaR	108	0.8594	6.5722	0.5600	1.3447	−15.8987	22.5513
BLVaR	108	0.6098	5.5144	0.3709	0.9723	−12.1159	19.5520
Panel D: Size–CVaR Portfolios							
SHCVaR	108	2.0675	7.9132	0.8957	2.0938	−16.5879	33.8711
SMCVaR	108	1.0438	4.9517	0.2143	0.5039	−13.6115	14.1425
SLCVaR	108	0.8444	4.3815	1.3624	5.5388	−7.4978	23.6924
BHCVaR	108	0.0502	6.9965	0.2863	0.7866	−18.0755	23.6611
BMCVaR	108	0.4175	6.2247	0.6678	1.2541	−14.0776	22.2356
BLCVaR	108	1.0886	5.6819	0.3157	0.5688	−12.1569	18.2773
Panel E: Size–Illiquidity Portfolios							
SHIlliq	108	1.5385	4.6995	0.6003	0.6978	−11.0515	15.0254
SMIlliq	108	1.3895	5.8721	1.0050	3.8745	−12.4658	29.6465
SLIlliq	108	0.6671	11.8869	0.8821	2.4856	−23.7851	52.4383
BHIlliq	108	0.0490	4.9359	0.5873	1.1580	−11.6327	16.2567
BMIlliq	108	0.6607	5.1535	0.3317	1.0156	−15.5646	15.2566
BLIlliq	108	0.7523	5.5732	0.3822	0.4670	−12.0964	17.8902
Panel F: Size–CAPM Beta Portfolios							
SHCAPM	108	1.5010	8.2580	1.0634	3.1869	−19.8701	35.2406
SMCAPM	108	1.0184	5.3589	0.7567	1.6409	−11.4535	21.2048
SLCAPM	108	1.6111	5.0489	1.1887	2.5434	−6.7857	23.8431
BHCAPM	108	0.4798	7.4707	0.8904	2.5490	−15.4220	29.5392
BMCAPM	108	0.7251	6.8260	0.5684	1.3402	−20.2201	21.2771
BLCAPM	108	0.5458	4.8761	0.0103	−0.1292	−11.0033	12.6571
Panel G: Size–DCC Beta Portfolios							

Statistics / Portfolios	N	Mean	St. Dev.	Skewness	Excess Kurtosis	Min	Max
SHDCC	108	1.4467	10.0654	0.9883	2.7952	−21.9848	43.3468
SMDCC	108	1.0526	5.4980	0.2808	1.4304	−15.2772	21.0370
SLDCC	108	1.4170	4.3229	0.9435	1.2717	−7.5386	15.6703
BHDCC	108	0.4281	7.0484	0.6577	1.1350	−14.9792	22.6746
BMDCC	108	1.1251	5.0966	0.3737	−0.1098	−9.5594	15.2017
BLDCC	108	0.0132	3.9114	0.1435	0.6917	−12.1070	11.0827

Notes: These portfolios are constructed using double sorting. The first sort is the firm size and the second sort is firm value, momentum, VaR, CVaR, illiquidity, CAPM beta, or DCC beta. The details of portfolio constructions are shown in Chapter 3. Descriptive statistics of monthly excess returns of portfolios are calculated from January 2011 to December 2019.

4.5.2.3. Size–Momentum Portfolios

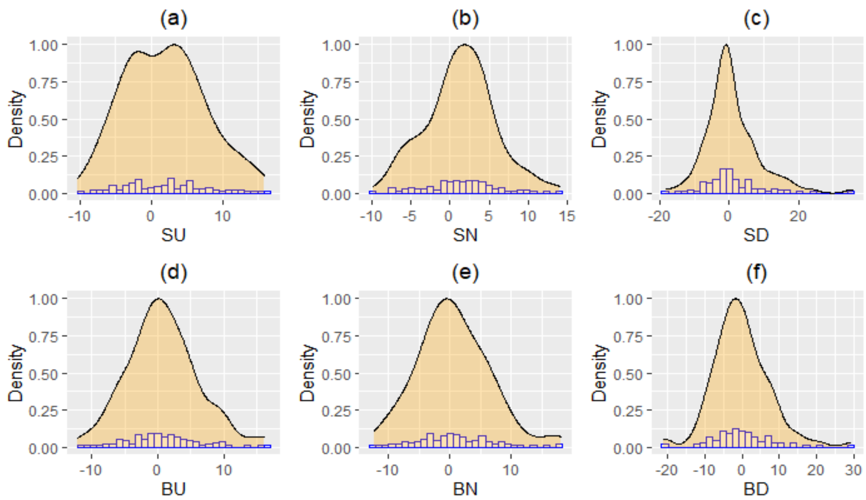


Figure 4.7: Distributions of Monthly Excess Returns of Size–Momentum Portfolios

Only the average monthly excess return of the BD portfolio is negative, other portfolios have positive returns (see Panel B, Table 4.7). The standard deviations of excess monthly returns of Size–Momentum portfolios fluctuate from approximately 4.5 per cent to 7.8 per cent. All Size–Momentum portfolios are right skewed because of positive skewness. While the SU portfolio has thinner tails than the normal distribution because of negative excess kurtosis, other portfolios have heavier tails than the normal distribution because of positive excess kurtosis.

The distribution of the SU portfolio is platykurtic; however, other portfolios are leptokurtic (see Figure 4.7).

4.5.2.4. Size–VaR Portfolios

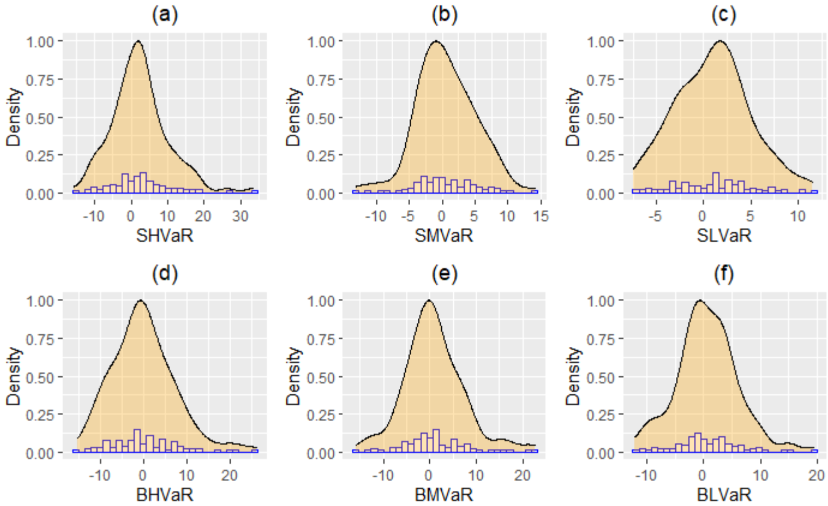


Figure 4.8: Distributions of Monthly Excess Returns of Size–VaR Portfolios

The average monthly excess returns of six Size–VaR portfolios are between 0.03 per cent and 2.38 per cent (see Panel C, Table 4.7). The standard deviations of excess monthly returns of Size–VaR portfolios fluctuate from approximately 4 per cent to 8 per cent. All Size–VaR portfolios are right skewed because of positive skewness. While the SLVaR portfolio has thinner tails than the normal distribution because of the negative excess kurtosis, other portfolios have heavier tails than the normal distribution because of the positive excess kurtosis. The distribution of the SLVaR portfolio is platykurtic; however, other portfolios are leptokurtic (see Figure 4.8).

4.5.2.5. Size–CVaR Portfolios

The smallest and highest average monthly excess returns of six Size–CVaR portfolios are approximately 0.05 per cent (BHCVaR portfolio), and 2.07 per cent (SHCVaR portfolio) (see Panel D, Table 4.7). The standard deviations of excess monthly returns of Size–CVaR portfolios fluctuate from approximately 4.4 per cent to 7.9 per cent. All Size–CVaR portfolios are right skewed, and they have heavier tails than the normal distribution because of positive both skewness and excess kurtosis. The distributions of all six Size–CVaR portfolios are leptokurtic and are shown in Figure 4.9.

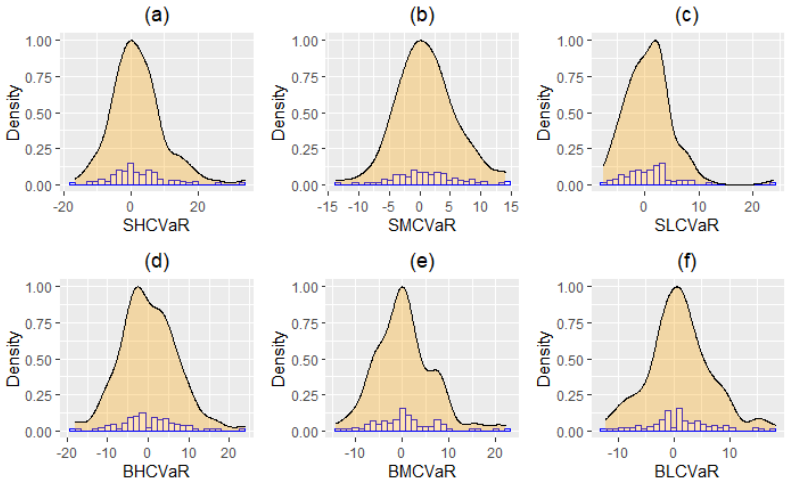


Figure 4.9: Distributions of Monthly Excess Returns of Size–CVaR Portfolios

4.5.2.6. Size–Illiquidity Portfolios

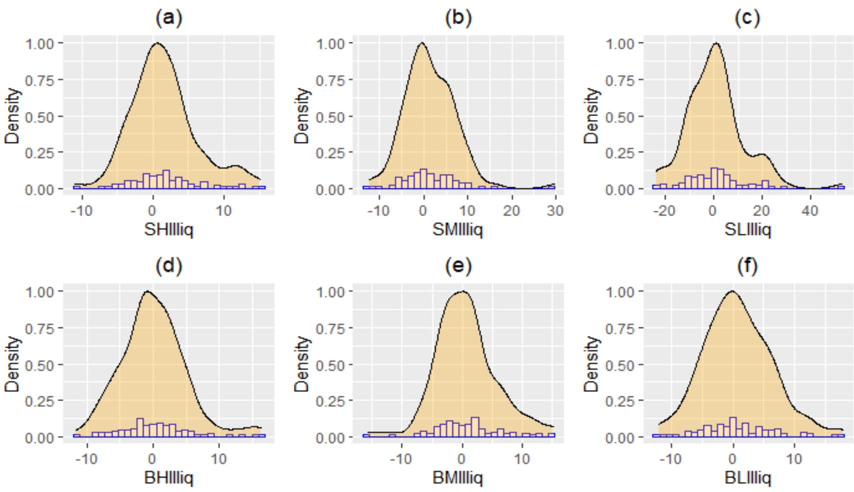


Figure 4.10: Distributions of Monthly Excess Returns of Size–Illiquidity Portfolios

The average monthly excess returns of six Size–Illiquidity portfolios are positive and between 0.05 per cent and 1.5 per cent (see Panel E, Table 4.7). The standard deviations of excess monthly returns of Size–Illiquidity portfolios fluctuate from approximately 4.7 per cent to 11.9 per cent. All Size–Illiquidity portfolios are right skewed, and they have heavier tails than the normal distribution because of positive both skewness and excess kurtosis. The distributions of all six Size–Illiquidity portfolios are leptokurtic and are shown in Figure 4.10.

4.5.2.7. Size–CAPM Beta Portfolios

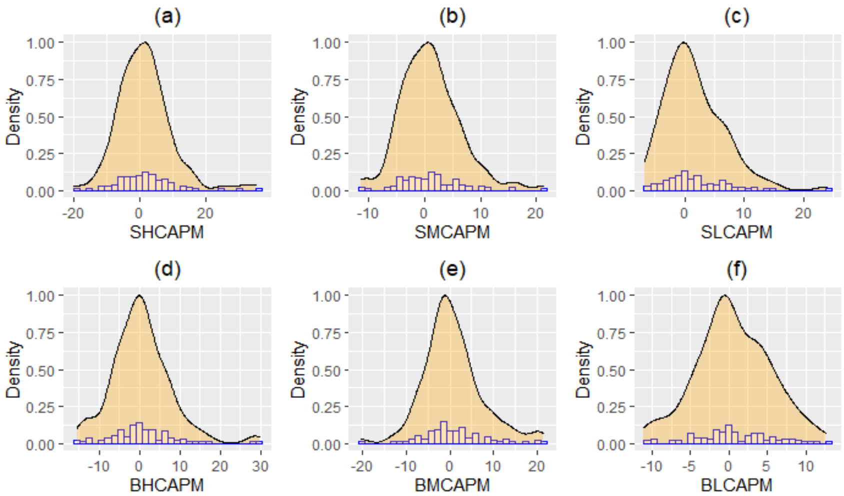


Figure 4.11: Distributions of Monthly Excess Returns of Size–CAPM Beta Portfolios

The average monthly excess returns of six Size–CAPM beta portfolios are positive and between 0.5 per cent and 1.6 per cent (see Panel F, Table 4.7). The standard deviations of excess monthly returns of Size–CAPM beta portfolios fluctuate from approximately 4.9 per cent to 8.2 per cent. All Size–CAPM beta portfolios are right skewed because of positive skewness. While the BLCAPM portfolio has thinner tails than the normal distribution because of the negative excess kurtosis, other portfolios have heavier tails than the normal distribution because of the positive excess kurtosis. The distribution of the BLCAPM portfolio is platykurtic; however, other portfolios are leptokurtic (see Figure 4.11).

4.5.2.8. Size–DCC Beta Portfolios

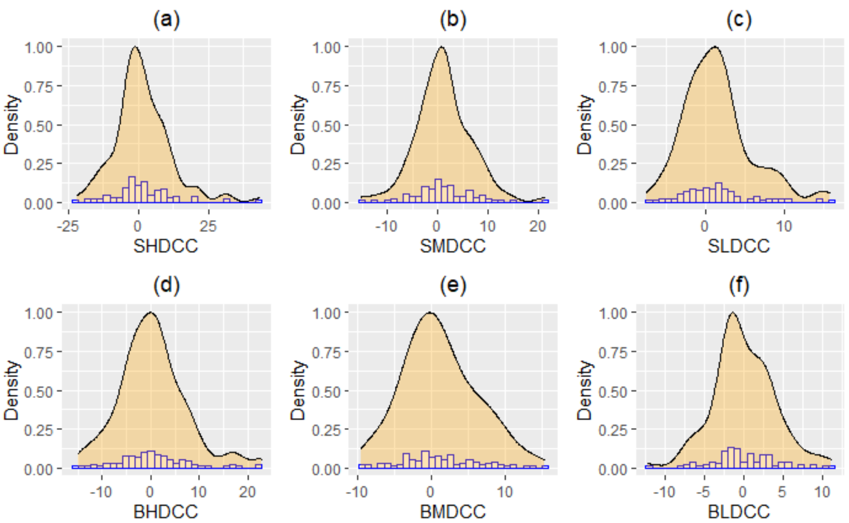


Figure 4.12: Distributions of Monthly Excess Returns of Size–DCC Beta Portfolios

The average monthly excess returns of six Size–DCC beta portfolios are positive and between 0.01 per cent and 1.5 per cent (see Panel G, Table 4.7). The standard deviations of excess monthly returns of Size–DCC beta portfolios fluctuate from approximately 3.9 per cent to 10.1 per cent. All Size–DCC Beta portfolios are right skewed because of positive skewness. While the BMDCC portfolio has thinner tails than the normal distribution because of the negative excess kurtosis, other portfolios have heavier tails than the normal distribution because of the positive excess kurtosis. The distribution of the BMDCC portfolio is platykurtic; however, other portfolios are leptokurtic (see Figure 4.12).

4.6. Normal Distribution Test

4.6.1. Stock Returns and Firm Characteristics

Although scaling, transformation and winsorisation are applied to reduce the outliers, monthly stock return and firm characteristics are still skewed and have thicker or thinner tails than normal distributions. The Jarque–Bera (JB) test (Tsay, 2012) for monthly return and firm characteristics from January 2011 to December 2019 in Table 4.8 confirms that these variables are not normal distributions because the skewness and excess kurtosis are not zeros simultaneously. The p-values of the tests are much less than 5 per cent. Therefore, the null hypothesis that these variables are normal distributions is rejected. The observations in the QQ plots in Figure 4.13 diverge sharply from straight lines, especially at the ends of the lines. This shows the distributions of the panel sample data against the expected normal distributions (Tsay, 2012).

Table 4.8: The JB Test for Monthly Stock Returns and Firm Characteristics

JB Test / Variables	Chi-squared	p-value
Monthly Return	14,240	< 2.2E-16
CAPM Beta	13.241	0.001333
DCC Beta	1241.6	< 2.2E-16
Firm Size	1,128.1	< 2.2E-16
Firm Value	574.24	< 2.2E-16
Momentum	52,557	< 2.2E-16
VaR	3,564.4	< 2.2E-16
CVaR	2,029.9	< 2.2E-16
Illiquidity	450.01	< 2.2E-16

Notes: The JB test is conducted on monthly returns and firm characteristics from January 2011 to December 2019. The null hypothesis of the JB test is that the variables are normally distributed.

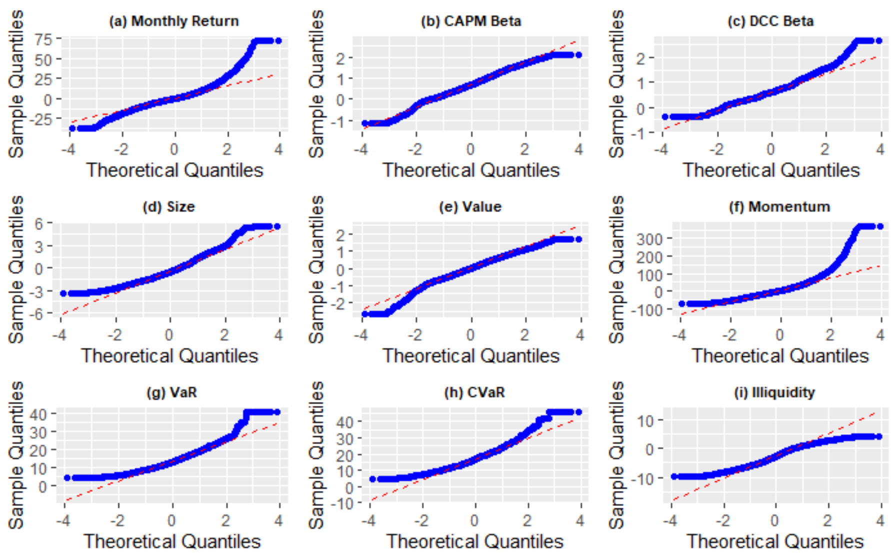


Figure 4.13: Q-Q Plots of Monthly Stock Returns and Firm Characteristics

4.6.2. Portfolio Returns and Risk Factors

4.6.2.1. Risk Factors

Table 4.9: The JB Test for Common Risk Factors

Variables \ JB Test	Chi-squared	p-value
MKT	0.7659	0.6819
SMB	3.8954	0.1426
HML	0.4443	0.8008
UMD	5.1077	0.0778
HVaRL	1.277	0.5281
LCVaRH	0.3805	0.8268
HILLIQL	3.1224	0.2099
RMW	1.9064	0.3855
CMA	0.1712	0.918

Notes: The JB test is conducted on monthly returns of risk factors from January 2011 to December 2019. The null hypothesis of the JB test is that the risk factors are normally distributed.

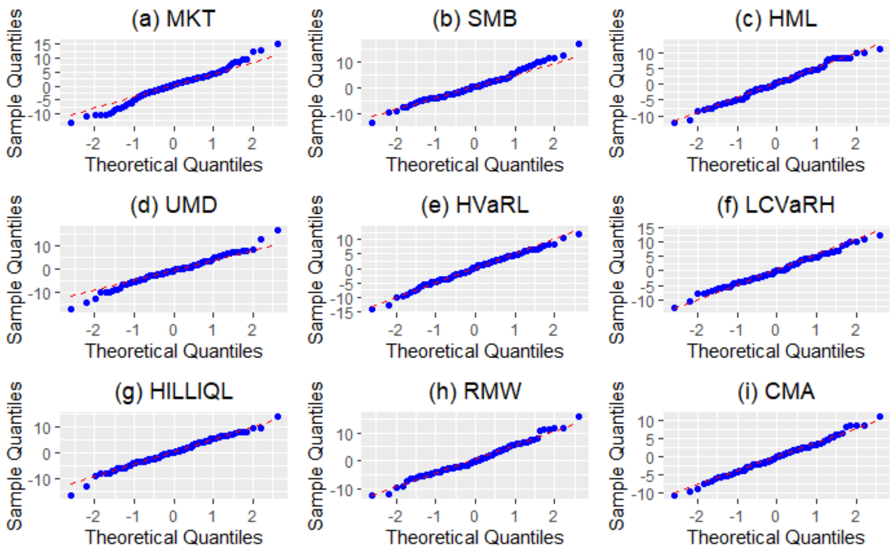


Figure 4.14: Q-Q Plots of Risk Factors

Table 4.9 shows the Jarque–Bera (JB) test (Tsay, 2012) for monthly returns of risk factors from January 2011 to December 2019. The null hypothesis is that the monthly returns of each factor is the normal distribution. If the null hypothesis is rejected, the normal distribution is not satisfied for the risk factors. The tests show that the returns of all risk factors pass the JB test with high p-values. The observations in the QQ plots in Figure 4.14 are lying in a straight line. This shows the distributions of all risk factors are similar to the normal distributions (Tsay, 2012).

4.6.2.2. Portfolio Returns

Table 4.10 shows the Jarque–Bera (JB) test (Tsay, 2012) for excess monthly returns of different portfolios from January 2011 to December 2019. For the Size–Value portfolios (Panel A), the monthly excess returns of BH and BL portfolios pass the JB test because of high p-values, approximately 15 per cent and 21 per cent, respectively. In contrast, the excess returns of other Size–Value portfolios do not pass the JB test because of low p-values. The monthly excess returns of the BH and BL portfolios in Figure 4.15 are more linear than the excess returns of other Size–Value portfolios, especially at the ends of the lines. Therefore, while the monthly excess returns of BH and BL portfolios are similar to the normal distributions, the excess returns of other Size–Value portfolios are not normally distributed.

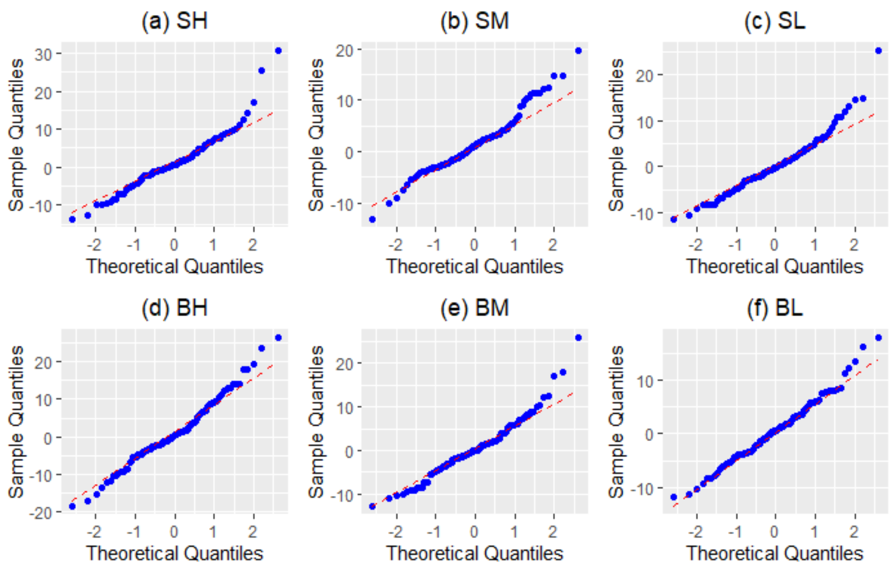


Figure 4.15: Q-Q Plots of Monthly Excess Returns of Size–Value Portfolios

Table 4.10: The JB Test for Portfolio Returns

JB Test / Portfolios	Chi-squared	p-value
Panel A: Size–Value Portfolios		
SH	73.135	< 2.2E-16
SM	9.5558	0.0084
SL	46.591	7.636E-11
BH	3.7898	0.1503
BM	31.179	1.697E-07
BL	3.0805	0.2143
Panel B: Size–Momentum Portfolios		
SU	2.4402	0.2952
SN	0.2534	0.881
SD	78.847	< 2.2E-16
BU	2.706	0.2585
BN	4.3238	0.1151
BD	24.953	3.815E-06
Panel C: Size–VaR Portfolios		
SHVaR	25.863	2.42E-06
SMVaR	1.7615	0.4145
SLVaR	0.7153	0.6993
BHVaR	15.59	0.0004
BMVaR	13.782	0.0010
BLVaR	6.7309	0.0345
Panel D: Size–CVaR Portfolios		
SHCVaR	34.167	3.807E-08
SMCVaR	1.9695	0.3735
SLCVaR	171.47	< 2.2E-16
BHCVaR	4.2594	0.1189
BMCVaR	15.106	0.0005
BLCVaR	3.2492	0.197
Panel E: Size–Illiquidity Portfolios		
SHIlliq	8.6769	0.0131
SMIlliq	85.732	< 2.2E-16
SLIlliq	41.808	8.348E-10
BHIlliq	12.243	0.0022
BMIlliq	6.6214	0.0365
BLIlliq	3.6103	0.1645

Portfolios \ JB Test	Chi-squared	p-value
Panel F: Size–CAPM Beta Portfolios		
SHCAPM	66.059	4.552E-15
SMCAPM	22.424	1.351E-05
SLCAPM	54.544	1.432E-12
BHCAPM	43.508	3.568E-10
BMCAPM	13.897	0.0010
BLCAPM	0.0770	0.9622
Panel G: Size–DCC Beta Portfolios		
SHDCC	52.74	3.529E-12
SMDCC	10.627	0.005
SLDCC	23.302	8.711E-06
BHDCC	13.582	0.0011
BMDCC	2.5682	0.2769
BLDCC	2.5234	0.2832

Note: The JB test is conducted on monthly excess returns of portfolios from January 2011 to December 2019. The null hypothesis of the JB test is that the portfolio returns are normally distributed.

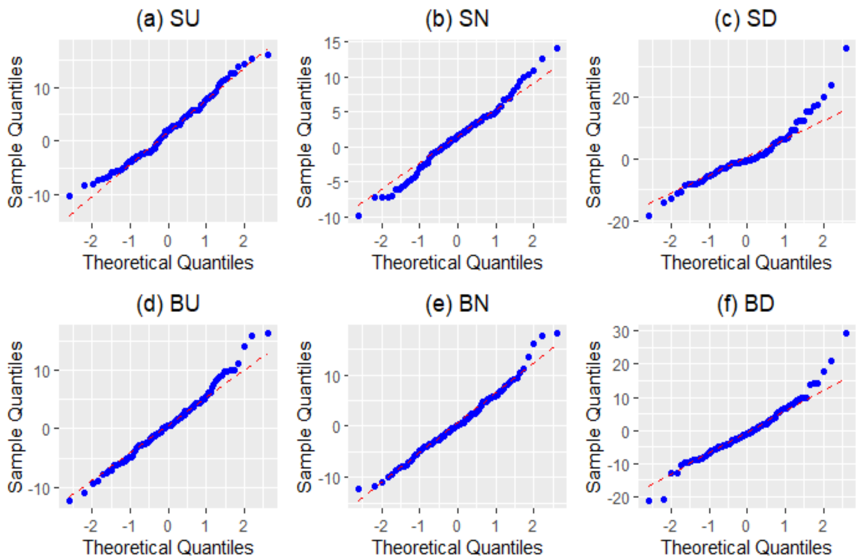


Figure 4.16: Q-Q Plots of Monthly Excess Returns of Size–Momentum Portfolios

For Size–Momentum portfolios (Panel B), only the monthly excess returns of the SD and BD portfolios do not pass the JB test because of the low p-values, the excess returns of other Size–

Momentum portfolios pass the JB test with high p-values (higher than 10%). The monthly excess returns of the SD and BD portfolios in Figure 4.16 diverge sharply from straight lines, especially at the ends of the lines, while the excess returns of other Size–Momentum portfolios are closely linear. Therefore, while the monthly excess returns of SD and BD portfolios are not normally distributed, the excess returns of other Size–Momentum portfolios are similar to the normal distributions.

For Size–VaR portfolios (Panel C), the monthly excess returns of SMVaR and SLVaR portfolios pass the JB test because of high p-values, approximately 41 per cent and 70 per cent, respectively. In contrast, the excess returns of other Size–VaR portfolios do not pass the JB test because of low p-values (less than 5%). The monthly excess returns of the SMVaR and SLVaR portfolios in Figure 4.17 are more linear than excess returns of other Size–VaR portfolios, especially at the ends of the lines. Therefore, while the monthly excess returns of SMVaR and SLVaR portfolios are similar to the normal distributions, the excess returns of other Size–VaR portfolios are not normally distributed.

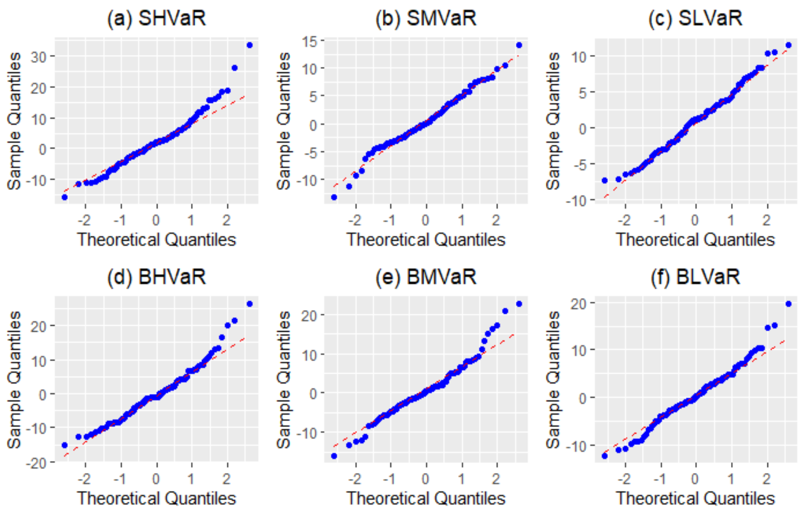


Figure 4.17: Q-Q Plots of Monthly Excess Returns of Size–VaR Portfolios

For Size–CVaR portfolios (Panel D), the monthly excess returns of SMCVaR, BHCVaR, and BLVaR portfolios pass the JB test because of high p-values (higher than 10%). In contrast, the excess returns of other Size–CVaR portfolios do not pass the JB test because of low p-values (less than 5%). The excess returns of the SMCVaR, BHCVaR, and BLVaR portfolios in Figure 4.18 are more linear than the excess returns of other Size–CVaR portfolios, especially at the ends of the lines. Therefore, while the monthly excess returns of SMCVaR, BHCVaR, and BLVaR portfolios are similar to the normal distributions, the excess returns of other Size–CVaR portfolios are not normally distributed.

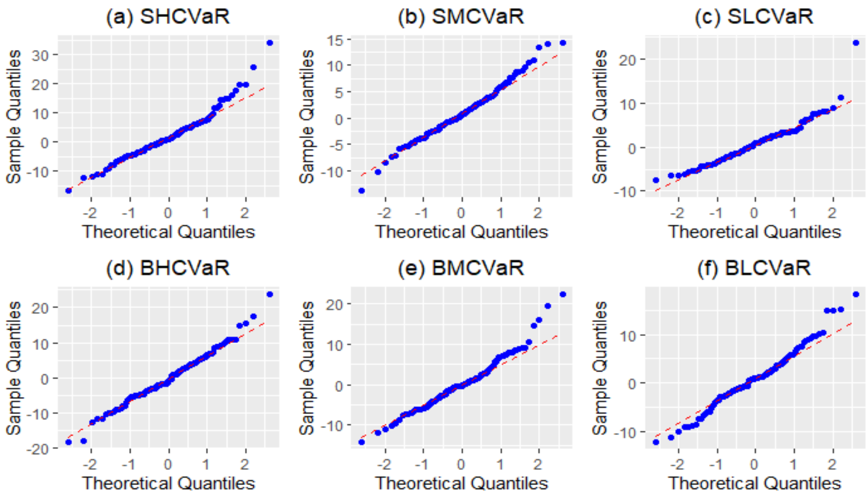


Figure 4.18: Q-Q Plots of Monthly Excess Returns of Size–CVaR Portfolios

For Size–Illiquidity portfolios (Panel E), only the monthly excess returns of the BLIlliq portfolio pass the JB test because of high p-values (approximately 16%). In contrast, the excess returns of other Size–Illiquidity portfolios do not pass the JB test because of low p-values (less than 5%). The excess returns of the BLIlliq portfolio in Figure 4.19 are more linear than the excess returns of other Size–Illiquidity portfolios, especially at the ends of the lines. Therefore, while the monthly excess returns of the BLIlliq portfolio are similar to the normal distributions, the excess returns of other Size–Illiquidity portfolios are not normally distributed.

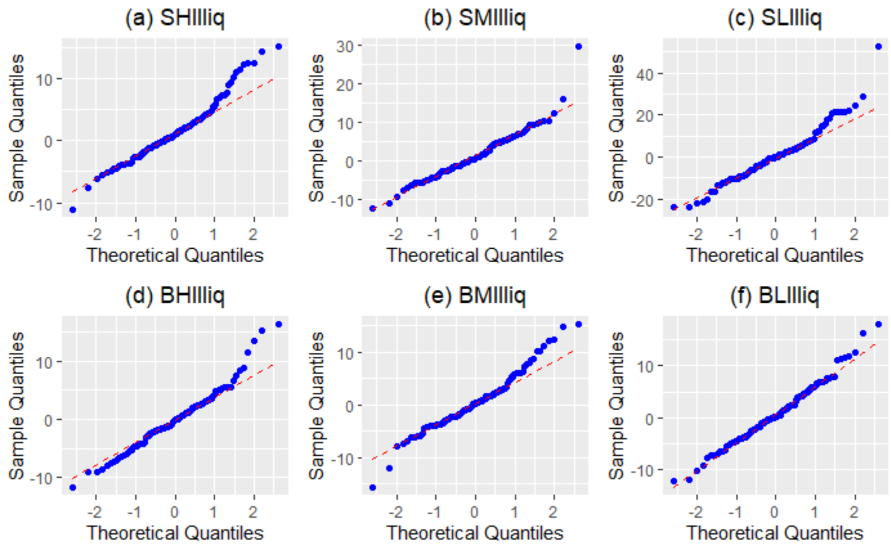


Figure 4.19: Q-Q Plots of Monthly Excess Returns of Size–Illiquidity Portfolios

For Size–CAPM beta portfolios (Panel F), only the monthly excess returns of the BLCAPM portfolio pass the JB test because of high p-values (approximately 16%). In contrast, the excess returns of other Size–CAPM beta portfolios do not pass the JB test because of low p-values (less than 5%). The excess returns of the BLCAPM portfolio in Figure 4.20 are more linear than the excess returns of other Size–CAPM beta portfolios, especially at the ends of the lines. Therefore, while the monthly excess returns of the BLCAPM portfolio are similar to the normal distributions, the returns of other Size–CAPM beta portfolios are not normally distributed.

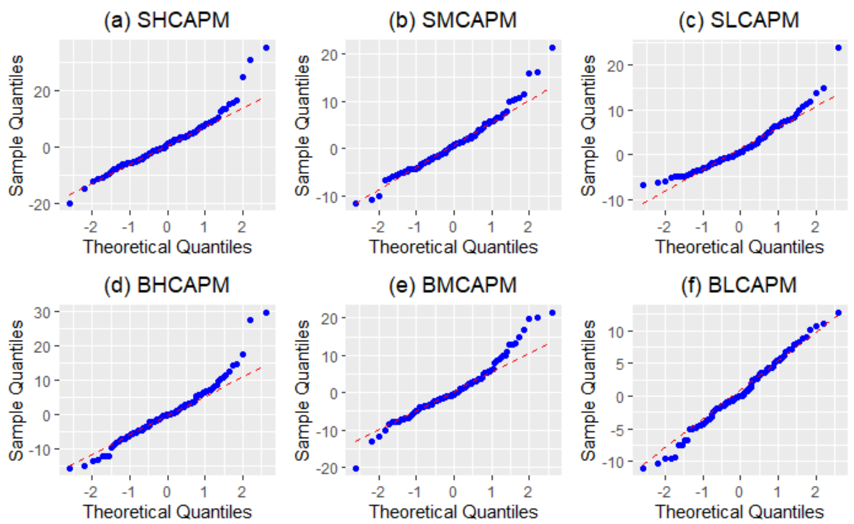


Figure 4.20: Q-Q Plots of Monthly Excess Returns of Size–CAPM Beta Portfolios

For Size–DCC beta portfolios (Panel G), only the monthly excess returns of the BMDCC and BLDCC portfolios pass the JB test because of high p-values (approximately 27% and 28%, respectively). In contrast, the excess returns of other Size–DCC beta portfolios do not pass the JB test because of low p-values (less than 5%). The excess returns of the BMDCC and BLDCC portfolios in Figure 4.21 are more linear than the excess returns of other Size–DCC beta portfolios, especially at the ends of the lines. Therefore, while the monthly excess returns of BMDCC and BLDCC portfolios are similar to the normal distributions, the excess returns of other Size–DCC beta portfolios are not normally distributed.

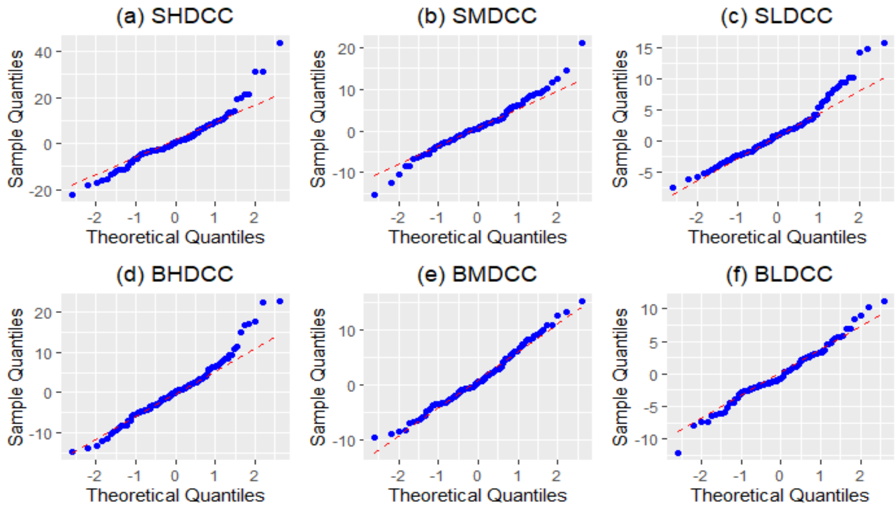


Figure 4.21: Q-Q Plots of Monthly Excess Returns of Size–DCC Beta Portfolios

4.7. Unit Root Tests

4.7.1. Stock Returns and Firm Characteristics

Table 4.11 shows the Levin–Lin–Chu (LLC) test (Levin et al., 2002) for the panel data of monthly returns and firm characteristics of 100 stocks from January 2011 to December 2019. The results show that monthly returns, CAPM beta, DCC beta, momentum, VaR, CVaR, and illiquidity pass the LLC test because of low p-values compared to 1 per cent, 5 per cent, and

10 per cent levels. This rejects the null hypothesis of a unit root in the panel data of these variables. This means monthly return, CAPM beta, DCC beta, momentum, VaR, CVaR, and illiquidity of all stocks are stationary. The firm size passes the LLC test at a 5 per cent level; however, they fail at a 1 per cent level. The firm value variable does not pass the LLC test because of a high p-value (approximately 43%); therefore, this variable is non-stationary.

Table 4.11: The LLC Test for Monthly Stock Returns and Firm Characteristics

LLC Test / Variables	Z	p-value
Monthly Returns	−6.1873	3.059E-10
CAPM Beta	−7.8309	2.421E-15
DCC Beta	−2.7703	0.0028
Firm Size	−1.678	0.0467
Firm Value	−0.1716	0.4319
Momentum	−34.999	< 2.2E-16
VaR	−6.8579	3.494E-12
CVaR	−6.7986	5.281E-12
Illiquidity	−13.281	< 2.2E-16

Notes: The LLC test is conducted on monthly returns and firm characteristics from January 2011 to December 2019. The null hypothesis of the LLC test is that there exists a unit root in these variables.

4.7.2. Portfolio Returns and Risk Factors

4.7.2.1. Risk Factors

Table 4.12 shows the Augmented Dickey–Fuller (ADF) test (Wooldridge, 2012) for nine risk factors from January 2011 to December 2019. The results show that all p-values of DF statistics are lower than 1 per cent. Therefore, the null hypothesis that a unit root has existed in risk factors is rejected. In other words, the monthly returns of these factors can be considered stationary processes.

Table 4.12: The ADF Test for Monthly Returns of Risk Factors

Variables \ ADF Test	DF	p-value
MKT	−4.907	<0.01
SMB	−4.3389	<0.01
HML	−5.499	<0.01
UMD	−4.5824	<0.01
HVaRL	−5.6054	<0.01
LCVaRH	−4.9002	<0.01
HILLIQL	−4.3926	<0.01
RMW	−5.7103	<0.01
CMA	−5.539	<0.01

Notes: The ADF test is conducted on monthly returns of risk factors from January 2011 to December 2019. The null hypothesis of the ADF test is that there exists a unit root in returns of risk factors.

4.7.2.2. Portfolio Returns

Table 4.13: The ADF Test for Portfolio Excess Monthly Returns

Portfolios \ ADF Test	DF	p-value
Panel A: Size–Value Portfolios		
SH	−5.5579	0.01
SM	−6.3255	0.01
SL	−6.6919	0.01
BH	−5.8401	0.01
BM	−6.1948	0.01
BL	−5.1529	0.01
Panel B: Size–Momentum Portfolios		
SU	−5.2157	0.01
SN	−6.0361	0.01
SD	−5.5304	0.01
BU	−4.7261	0.01
BN	−5.4506	0.01
BD	−6.6922	0.01
Panel C: Size–VaR Portfolios		
SHVaR	−5.538	0.01
SMVaR	−6.498	0.01

Portfolios \ ADF Test	DF	p-value
SLVaR	−5.3863	0.01
BHVaR	−6.4968	0.01
BMVaR	−5.6227	0.01
BLVaR	−4.8258	0.01
Panel D: Size–CVaR Portfolios		
SHCVaR	−5.5134	0.01
SMCVaR	−5.9444	0.01
SLCVaR	−5.3357	0.01
BHCVaR	−6.5957	0.01
BMCVaR	−5.9236	0.01
BLCVaR	−4.7321	0.01
Panel E: Size–Illiquidity Portfolios		
SHIlliq	−4.8178	0.01
SMIlliq	−6.2293	0.01
SLIlliq	−4.5976	0.01
BHIlliq	−5.1336	0.01
BMIlliq	−5.5617	0.01
BLIlliq	−5.3733	0.01
Panel F: Size–CAPM Beta Portfolios		
SHCAPM	−5.3173	0.01
SMCAPM	−5.8564	0.01
SLCAPM	−4.7187	0.01
BHCAPM	−6.6454	0.01
BMCAPM	−5.5183	0.01
BLCAPM	−4.6651	0.01
Panel G: Size–DCC Beta Portfolios		
SHDCC	−5.8846	0.01
SMDCC	−6.0167	0.01
SLDCC	−4.9814	0.01
BHDCC	−5.8383	0.01
BMDCC	−4.6641	0.01
BLDCC	−5.6496	0.01

Notes: The ADF test is conducted on excess monthly returns of portfolios from January 2011 to December 2019. The null hypothesis of the ADF test is that there exists a unit root in portfolio returns.

Table 4.13 shows the augmented Dickey-Fuller (ADF) tests (Wooldridge, 2012) for monthly excess returns of portfolios constructed by different combinations: firm size and firm value (Panel A), firm size and momentum (Panel B), firm size and VaR (Panel C), firm size and CVaR (Panel D), firm size and illiquidity (Panel E), firm size and CAPM beta (Panel F), firm size and DCC beta (Panel G) from January 2011 to December 2019. The null hypothesis that a unit root has existed in risk factors is rejected because of low p-values. In other words, the monthly excess returns of these portfolios can be considered stationary processes.

4.8. Correlation

4.8.1. Stock Return and Firm Characteristics

Table 4.14: Correlations of Monthly Stock Returns and Firm Characteristics

	Monthly Return	**CAPM Beta**	**DCC Beta**	**Firm Size**	**Firm Value**	**Momentum**	**VaR**	**CVaR**	**Illiquidity**
Monthly Return	1								
CAPM Beta	−0.007	1							
DCC Beta	0.011	0.619	1						
Firm Size	−0.034	0.080	0.293	1					
Firm Value	0.074	0.149	0.093	−0.520	1				
Momentum	0.058	−0.020	0.075	0.157	0.217	1			
VaR	0.004	0.391	0.244	−0.256	0.216	−0.148	1		
CVaR	0.002	0.356	0.225	−0.268	0.235	−0.139	0.908	1	
Illiquidity	0.033	−0.380	−0.522	−0.717	0.187	−0.175	0.026	0.048	1

Notes: The correlations are computed from January 2011 to December 2019.

Table 4.14 shows the correlations between monthly stock returns and their firm characteristics calculated from January 2011 to December 2019. The correlation matrix represents the dependence between independent variables and dependent variables, as well as between independent variables. Overall, the dependent variable (monthly return) is weakly correlated with independent variables (CAPM beta, DCC beta, firm size, firm value, momentum, Value-at-Risk, and illiquidity). Some high correlations are detected between independent variables such as firm size and firm value, firm size and illiquidity, DCC beta and illiquidity (greater than -0.5), CAPM beta and DCC beta (greater than 0.6), VaR, and CVaR (greater than 0.9). The high correlations between independent variables may cause multicollinearity which reduces the efficiency of regressions. The multicollinearity is tested using VIF after running regressions.

4.8.2. Portfolio Returns and Risk Factors

4.8.2.1. Correlations between Risk Factors

Table 4.15: Correlations between Monthly Returns of Risk Factors

	MKT	SMB	HML	UMD	HVaRL	LCVaRH	HILLIQL	RMW	CMA
MKT	1								
SMB	−0.269	1							
HML	0.061	0.707	1						
UMD	−0.156	−0.478	−0.614	1					
HVaRL	0.158	0.576	0.725	−0.615	1				
LCVaRH	−0.115	−0.631	−0.757	0.582	−0.893	1			
HILLIQL	−0.507	0.708	0.510	−0.307	0.386	−0.442	1		
RMW	−0.081	−0.633	−0.814	0.634	−0.814	0.866	−0.475	1	
CMA	0.059	0.632	0.658	−0.573	0.659	−0.696	0.446	−0.648	1

Notes: The correlations are computed from January 2011 to December 2019.

Table 4.15 shows the correlations between monthly returns of nine risk factors calculated from January 2011 to December 2019. Overall, the HML, HVaRL, and CMA factors are moving in the same direction as the MKT (positive correlations) while the MKT and the other factors (SMB, UMD, LCVaRH, HILLIQL, and RMW) are moving in the opposite directions (negative correlations). However, all the correlations between the returns of the MKT factor and other factors are low. In contrast, the correlations between SMB, HML, UMD, HVaRL, LCVaRH, HILLIQL, RMW, and CMA are high. These high correlations may cause multicollinearity and reduce the effects of estimated coefficients in regressions. The problem of multicollinearity is further tested using VIF in Chapter 6.

4.8.2.2. Correlations between Portfolio Returns and Risk Factors

Table 4.16 shows the correlations between the monthly returns of 42 portfolios and nine risk factors calculated from January 2011 to December 2019. The higher correlations between portfolio returns and risk factors, the better the risk factors explain the asset returns. All portfolio returns and the MKT are moving in the same direction (positive correlations), and 29 correlations are higher than 0.5.

The SMB factor and 26 portfolio returns are moving in the same direction (positive correlations); however, only the correlation between the SLDCC portfolio and the SMB is significant (approximately 0.5). In contrast, 16 portfolio returns and the SMB are moving in opposite directions (negative correlations). In particular, four correlations between BL, BLVaR, BLCVaR, and BMDCC portfolios and the SMB are significant (less than −0.5).

Table 4.16: Correlations between Monthly Returns of Portfolios and Risk Factors

Portfolios \ Factors		**MKT**	**SMB**	**HML**	**UMD**	**HVaRL**	**LCVaRH**	**HILLIQL**	**RMW**	**CMA**
Size–Value Portfolios	SH	0.521	0.413	0.530	−0.456	0.513	−0.467	−0.084	−0.488	0.421
	SM	0.505	0.373	0.505	−0.509	0.484	−0.441	−0.024	−0.417	0.423
	SL	0.296	0.308	0.436	−0.238	0.277	−0.248	0.157	−0.375	0.315
	BH	0.633	0.102	0.511	−0.421	0.436	−0.379	−0.153	−0.413	0.378
	BM	0.725	−0.042	0.343	−0.290	0.312	−0.342	−0.349	−0.327	0.301
	BL	0.780	−0.541	−0.248	0.056	−0.126	0.219	−0.764	0.220	−0.239
Size–Momentum Portfolios	SU	0.446	0.248	0.401	−0.406	0.322	−0.268	−0.112	−0.290	0.303
	SN	0.510	0.358	0.501	−0.366	0.428	−0.363	−0.049	−0.424	0.351
	SD	0.496	0.406	0.511	−0.471	0.525	−0.508	0.011	−0.514	0.450
	BU	0.695	−0.449	−0.101	0.049	−0.066	0.112	−0.605	0.101	−0.144
	BN	0.770	−0.273	0.042	−0.149	0.120	−0.046	−0.539	−0.039	0.045
	BD	0.734	−0.083	0.220	−0.369	0.375	−0.320	−0.404	−0.324	0.230

Portfolios \ Factors		MKT	SMB	HML	UMD	HVaRL	LCVaRH	HILLIQL	RMW	CMA
Size–VaR Portfolios	SHVaR	0.526	0.414	0.541	−0.505	0.548	−0.516	−0.043	−0.533	0.459
	SMVaR	0.526	0.376	0.584	−0.441	0.480	−0.417	0.017	−0.473	0.405
	SLVaR	0.441	0.307	0.347	−0.362	0.286	−0.270	−0.079	−0.266	0.315
	BHVaR	0.692	0.020	0.392	−0.321	0.548	−0.522	−0.255	−0.452	0.289
	BMVaR	0.756	−0.178	0.118	−0.251	0.241	−0.169	−0.484	−0.209	0.168
	BLVaR	0.683	−0.537	−0.249	0.083	−0.241	0.279	−0.672	0.282	−0.243
Size–CVaR Portfolios	SHCVaR	0.491	0.432	0.552	−0.473	0.538	−0.492	−0.011	−0.518	0.473
	SMCVaR	0.596	0.320	0.509	−0.476	0.447	−0.432	−0.056	−0.478	0.425
	SLCVaR	0.338	0.341	0.402	−0.345	0.306	−0.262	−0.010	−0.257	0.245
	BHCVaR	0.717	−0.029	0.363	−0.330	0.524	−0.500	−0.269	−0.445	0.293
	BMCVaR	0.719	−0.078	0.233	−0.419	0.387	−0.315	−0.404	−0.293	0.291
	BLCVaR	0.693	−0.559	−0.299	0.182	−0.295	0.345	−0.734	0.312	−0.323
Size–Illiquidity Portfolios	SHIlliq	0.337	0.469	0.533	−0.436	0.443	−0.418	0.141	−0.474	0.323
	SMIlliq	0.585	0.350	0.492	−0.471	0.453	−0.424	−0.113	−0.427	0.458
	SLIlliq	0.426	0.270	0.386	−0.275	0.421	−0.363	−0.105	−0.383	0.273
	BHIlliq	0.103	0.152	0.307	−0.345	0.371	−0.373	0.268	−0.396	0.258
	BMIlliq	0.613	0.069	0.337	−0.302	0.301	−0.229	−0.120	−0.246	0.311
	BLIlliq	0.820	−0.488	−0.156	0.000	−0.054	0.127	−0.752	0.129	−0.163
Size–CAPM Beta Portfolios	SHCAPM	0.572	0.343	0.472	−0.428	0.515	−0.448	−0.083	−0.464	0.440
	SMCAPM	0.517	0.339	0.526	−0.473	0.462	−0.437	−0.068	−0.477	0.359
	SLCAPM	0.271	0.452	0.452	−0.352	0.340	−0.316	0.125	−0.331	0.326
	BHCAPM	0.803	−0.123	0.219	−0.270	0.324	−0.284	−0.449	−0.295	0.198
	BMCAPM	0.734	−0.151	0.157	−0.339	0.257	−0.161	−0.458	−0.177	0.195
	BLCAPM	0.489	−0.390	−0.145	0.122	−0.071	0.068	−0.472	0.058	−0.176
Size–DCC Beta Portfolios	SHDCC	0.634	0.262	0.458	−0.443	0.523	−0.464	−0.182	−0.446	0.415
	SMDCC	0.618	0.317	0.489	−0.495	0.465	−0.424	−0.069	−0.440	0.469
	SLDCC	0.164	0.514	0.543	−0.348	0.363	−0.352	0.156	−0.411	0.285
	BHDCC	0.852	−0.202	0.123	−0.278	0.257	−0.187	−0.512	−0.190	0.175
	BMDCC	0.595	−0.557	−0.310	0.195	−0.240	0.311	−0.736	0.336	−0.323
	BLDCC	0.225	0.131	0.287	−0.260	0.355	−0.281	0.243	−0.331	0.222

Notes: The correlations are computed from January 2011 to December 2019.

The HML factor and 35 portfolio returns are moving in the same direction; however, only 12 correlations between SH, SM, BH, SN, SD, SHVaR, SMVaR, SHCVaR, SMCVaR, SHIlliq, SMCAPM, SLDCC portfolios and the HML are significant (higher than 0.5). In contrast, seven portfolio returns and this factor are moving in opposite directions. However, all the negative correlations are weak (higher than −0.5).

The UMD factor and six portfolio returns are moving in the same direction; however, all the positive correlations are weak and below 0.5. In contrast, 36 portfolio returns and the UMD are moving in opposite directions. In particular, two correlations between SM and SHVaR portfolios and the UMD are significant (less than −0.5).

The HVaRL factor and 35 portfolio returns are moving in the same direction; however, only eight correlations between SH, SD, SHVaR, BHVaR, SHCVaR, BHCVaR, SHCAPM, and SHDCC portfolios and the HVaRL are significant (higher than 0.5). In contrast, seven portfolio returns and the HVaRL are moving in opposite directions. However, all the negative correlations are weak (higher than −0.5).

The LCVaRH factor and seven portfolio returns are moving in the same direction; however, all the positive correlations are weak and below 0.5. In contrast, 35 portfolio returns and the LCVaRH are moving in opposite directions. In particular, three correlations between SD, SHVaR, and BHVaR portfolios and the LCVaRH are significant (less than −0.5).

The HILLIQL factor and eight portfolio returns are moving in the same direction; however, all the positive correlations are weak and below 0.5. In contrast, 34 portfolio returns and the HILLIQL are moving in opposite directions. In particular, eight correlations between BL, BU, BN, BLVaR, BLCVaR, BLIlliq, BHDCC, and BMDCC portfolios and the HILLIQL are significant (less than −0.5).

The RMW factor and seven portfolio returns are moving in the same direction; however, all the positive correlations are weak and below 0.5. In contrast, 35 portfolio returns and the RMW are moving in opposite directions. In particular, three correlations between SD, SHVaR, and SHCVaR portfolios and the RMW are significant (less than −0.5).

The CMA factor and 35 portfolio returns are moving in the same direction while only seven portfolio returns and the CMA are moving in opposite directions. However, all the negative and positive correlations are weak.

4.9. Conclusion

This chapter shows that the Vietnam stock market is immature. Listing and registering stocks are traded on the system of the stock exchanges with buy and sell orders; however, the price and volume of each order are controlled. Also, the chapter explains why accounting and financial data are non-normal distributions. Understanding this issue, the sample data are scaled, transformed, and winsorised to make them more symmetric and lessen outliers. Although these techniques reduce the outliers and make the data more balanced, they are still skewed and have thicker or thinner tails compared to normal distributions. Some issues of unit root and high correlations are detected in the firm characteristics. Therefore, different regression techniques and robustness are applied for further analyses.

Although firm characteristics are skewed and not normally distributed, all risk factors are less skewed and similar to the normal distribution. In contrast to the stock returns and firm characteristics, the portfolio returns and risk factors all pass the unit root test. However, high correlations are found in the risk factors. Therefore, multicollinearity may exist and affect the risk factors in explaining portfolio returns. The multicollinearity is detected using VIF and risk factors that have high VIF can be removed.

Chapter 5: Testing the Relation Between Firm Characteristics and Stock Returns

5.1. Introduction

Based on the literature, Chapter 3 hypothesises that stock returns are negatively correlated with firm size and conditional Value-at-Risk (CVaR), while stock returns are positively correlated with CAPM beta, DCC beta, firm value, momentum, illiquidity, and Value-at-Risk (VaR). This chapter tests these hypotheses using different methods: OLS, between estimators (BE), Fama–MacBeth (FM), and panel regressions.

Researchers often use different data structures such as cross-sectional data, time series, and panel data for empirical tests in corporate finance and asset pricing (Petersen, 2009). The most popular method to study the cross-section of stock returns is to use Fama–MacBeth (FM) regression on panel data (Fama, 2014; Hanauer & Lauterbach, 2019; Harvey et al., 2016; Mclean & Pontiff, 2016; Petersen, 2009). However, this method has a limitation called "errors-in-variables" (sampling errors in estimations using historical data) (Ang et al., 2020; Bhandari, 1988; Claessens et al., 1995; Fama & MacBeth, 1973; Jagannathan & Wang, 2002). Hanck et al. (2021) explain that when independent variables are estimated using historical data, these variables can be different from the population. Therefore, this causes measurement error (error-in-variables bias). The between-estimator (BE) model which transforms variables of the panel into individual means (cross-sectional data) can reduce this error (Claessens et al., 1995).

Croissant and Millo (2018) show that panel data have more features and advantages over cross-sectional and time-series data. These authors also state that the advantages of panel data identify different effects (individual effects, time effects, or both effects) that cross-sectional and time series cannot detect. Furthermore, panel data use two dimensions (individual and time dimensions). Therefore, panel data improves the measurement accuracy of cross-sectional and time series that use only one dimension to describe the data (Croissant & Millo, 2018). Currently, panel data are also widely used in finance. However, many published papers do not adjust the standard errors for individual, time, or both effects in the errors (Petersen, 2009). This may cause bias in estimations. Therefore, the standard errors of the slopes of all regressions in this chapter are robust and estimated using the traditional method developed by Newey and West (1987) and the latest clustering techniques (Fama, 2014; Millo, 2019; Petersen, 2009; Thompson, 2011).

5.2. Examining the Variations of Stock Returns and Firm Characteristics

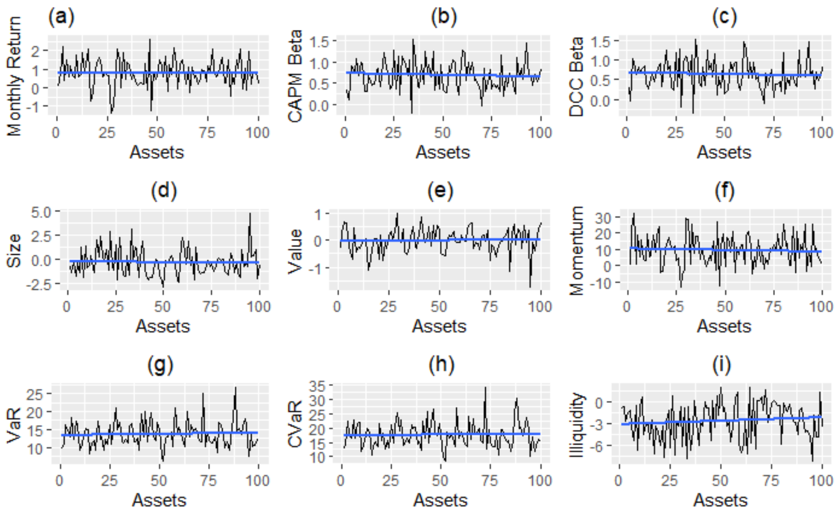


Figure 5.1: Heterogeneity Across 100 Assets

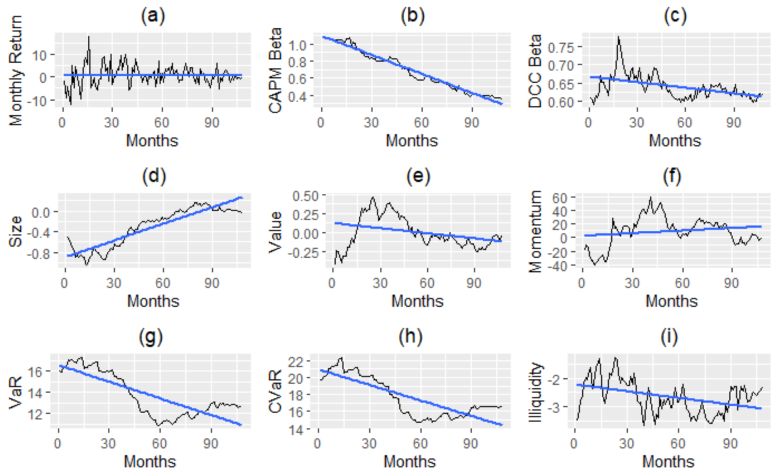


Figure 5.2: Heterogeneity Across 108 Months (January 2011 to December 2019)

Figures 5.1 and 5.2 show the mean of stock returns and firm characteristics across 100 assets and 108 months (from January 2011 to December 2019), respectively. The differences in the average of stock returns and firm characteristics are called heterogeneity. This issue may be caused by unobserved effects (individual, time, or both effects) that are fixed (fixed effects) or random draws from a distribution (random effects). Under the heterogeneity, the OLS estimation is not sufficient to control the effects of unobserved effects. Therefore, panel regressions which are allowing to control for heterogeneity are expected to enhance the OLS (Croissant & Millo, 2018). While Figure 5.1 shows that the averages of these variables are symmetric across 100 assets, Figure 5.2 shows their means are asymmetrical across 108 months (from January 2011 to December 2019). The green lines are simple linear regression on these means to show the symmetric of the data.

5.3. Multicollinearity Tests among Firm Characteristics

This chapter tests the cross-section of stock returns and firm characteristics using different methods of estimation: OLS, BE, FM, FE, RE on two models (1a) and (1b). Model (1a) runs the regression between monthly stock returns and CAPM beta, firm size, firm value, momentum, illiquidity, and Value-at-Risk. In contrast, model (1b) uses DCC beta and CVaR to alternate the CAPM beta and the VaR in model (1a), respectively. The variables and regression methods are discussed in Chapter 3. Descriptive statistics of these variables are shown in Chapter 4. Wooldridge (2012) recommends that for estimating coefficients, the correlations between independent variables should be small. Otherwise, multicollinearity (a high correlation between independent variables) will cause a large variance for the coefficients. To test the multicollinearity of independent variables, Wooldridge (2012) proposes using the variance inflation factors (VIFs). If a VIF of an independent variable is greater than 10, multicollinearity is an issue for estimating the coefficient for that variable. Table 5.1 shows the variance inflation factors (VIFs) of individual characteristics from January 2011 to December 2019.

Table 5.1: The VIFs of Individual Characteristics

Panel A: Model (1a)							
Estimations	**Variables**	**CAPM Beta**	**Size**	**Value**	**Momentum**	**VaR**	**Illiquidity**
OLS		1.5077	3.4110	1.7538	1.2089	1.3306	2.8015
BE		2.2601	5.3604	2.4138	1.2059	1.3179	5.3274
FM		1.1422	3.1350	2.1047	1.3934	1.2800	2.1804
FE	**Individual Effects**	1.5119	4.4804	2.1887	1.4284	1.6071	2.2690
	Time Effects	1.3782	1.8958	1.3911	1.1909	1.1880	1.7264
	Individual & Time Effects	1.7612	5.3617	2.4476	1.5407	1.6948	2.3583
RE	**Individual Effects**	1.3331	2.6245	1.9283	1.6491	1.4062	1.6982
	Time Effects	1.5052	3.3800	1.7138	1.1165	1.2085	2.8664
	Individual & Time Effects	1.2054	2.2815	1.8590	1.5569	1.1989	1.5395
Panel B: Model (1b)							
Estimations	**Variables**	**DCC Beta**	**Size**	**Value**	**Momentum**	**CVaR**	**Illiquidity**
OLS		1.5570	3.3752	1.7988	1.2027	1.2384	2.7635
BE		2.2496	5.2297	2.4590	1.2396	1.3063	5.1544
FM		1.1146	3.5364	1.8395	1.4047	1.0958	2.5172
FE	**Individual Effects**	2.7057	4.3170	2.1792	1.4404	1.5675	2.1944
	Time Effects	1.2558	1.8932	1.4016	1.1898	1.1603	1.7086
	Individual & Time Effects	2.7396	5.2649	2.4154	1.5472	1.6553	2.3002
RE	**Individual Effects**	1.1765	2.5698	1.9156	1.6104	1.2875	1.6371
	Time Effects	1.5662	3.3697	1.7410	1.1142	1.1779	2.8095
	Individual & Time Effects	1.1233	2.2482	1.8243	1.5472	1.1534	1.4692

Notes: The VIFs are computed for firm characteristics from January 2011 to December 2019 for different estimations. If VIF is greater than 10, high multicollinearity is detected. Otherwise, the multicollinearity is rejected.

Table 5.1 shows that firm size has higher VIFs than the other variables; however, all VIF values are quite low compared to 10. Therefore, multicollinearity is rejected in all estimations. In other words, it indicates the collinearity between these individual characteristics is low and this increases the statistical significance of these variables in explaining stock returns.

5.4. Model Estimations

Tables 5.2 and 5.3 show the results of five regressions including OLS regression, between-estimator (BE) regression, Fama–MacBeth (FM) regression, fixed effects (FE), and random effects (RE) for two models (1a) and (1b) from January 2011 to December 2019. The OLS estimation does not consider the effects (individual, time, and both effects) in their error term. However, FE and RE estimations consider these effects in their models to estimate coefficients. While FE regression considers these effects are fixed, RE regression considers they are random in estimating coefficients. FM regressions are conducted in two steps. First, stock returns of each asset are regressed with firm characteristics over time to obtain the slopes. Second, stock returns of all assets are regressed with these slopes to determine the risk premium. This technique is called the mean group in panel regression (Croissant & Millo, 2018; Millo, 2019). Fama (2014) states that FM estimation is standard in testing asset pricing models that capture the cross-section of stock returns using the benefits of panel data. Petersen (2009) shows that FM estimation is designed to address time effects, but not individual effects. The BE estimation measures variations of individual means of panel data and it can reduce the errors-in-variables in FM estimation (Claessens et al., 1995).

Overall, the F statistics show that all estimations are appropriate. Furthermore, the BE estimation fits the model better than FM estimation and panel regressions using OLS and FE, and RE methods because of the highest adjusted R^2 in both models. However, the BE and FM estimations cannot measure the unobserved effects such as individual effects, time effects, or both effects. Therefore, the coefficients of BE and FM estimations can be biased if these effects exist. Furthermore, the statistical inferences of these coefficients can be inflated or deflated if there exists the nonnormality, serial correlation, and heteroskedasticity of the residuals (Croissant & Millo, 2018; Millo, 2019; Petersen, 2009). Hence, Section 5.5 tests the residuals of all estimations. Then, Section 5.6 uses robust standard error to increase the statistical inference of all coefficients. Next, Section 5.7 examines the fixed and random effects, also the individual effects, time effects, or both effects for panel regressions. Section 5.8 shows the appropriate models after robustness and explains the coefficients.

Table 5.2: Model 1a

$$\mathbf{R_{i,t+1}} = \boldsymbol{\gamma_0} + \boldsymbol{\gamma_1}\boldsymbol{\beta}_{\mathbf{i,t}}^{\boldsymbol{CAPM}} + \boldsymbol{\gamma_2}\mathbf{Size_{i,t}} + \boldsymbol{\gamma_3}\mathbf{Value_{i,t}} + \boldsymbol{\gamma_4}\mathbf{Mom_{i,t}} + \boldsymbol{\gamma_5}\mathbf{Illiq_{i,t}} + \boldsymbol{\gamma_6}\mathbf{VaR_{i,t}} + \boldsymbol{\varepsilon_i}$$

Models / **Coefficients**	**OLS**	**BE**	**FM**	**FE**			**RE**		
				Individual Effects	**Time Effects**	**Individual & Time Effects**	**Individual Effects**	**Time Effects**	**Individual & Time Effects**
Alpha	1.1945	0.2324	0.7698				1.2211	0.7427	−0.1556
	t = 3.7094* **	t = 1.4124	**t = 1.8967***				**t = 2.3593** **	t = 1.4102	**t = −2.0509** **
CAPM Beta	−0.0131	0.2866	−0.0532	−0.9212	−0.0218	0.2731	−0.5631	−0.0247	0.0118
	t = −0.0526	**t = 1.8406***	t = −0.1527	**t = −3.0275*** **	t = −0.0853	t = 0.8422	**t = −1.9185***	t = −0.0975	t = 0.3702
Firm Size (Size)	0.2494	0.0889	−0.0951	−1.7653	−0.0037	−3.2666	−0.6060	0.0108	−1.7568
	t = 1.9174*	t = 1.5437	t = −0.6084	**t = −5.6275*** **	t = −0.0299	**t = −9.5126*** **	**t = −2.5083** **	t = 0.0883	**t = −62.9246*** **
Firm Value (Value)	1.2775	−0.1234	0.2970	2.2888	0.4328	0.3109	2.6398	0.4809	1.1264
	t = 5.6180* **	t = −1.0423	t = 0.9238	**t = 6.1268*** **	**t = 1.9787** **	t = 0.8136	**t = 7.9394*** **	**t = 2.2048** **	**t = 31.8782*** **
Momentum	0.0110	0.0675	0.0165	0.0098	0.0092	0.0160	0.0053	0.0094	0.0092
	t = 4.4195* **	**t = 17.0077*** **	**t = 2.9350*** **	**t = 3.0440*** **	**t = 3.7377*** **	**t = 5.0347*** **	**t = 1.8135***	**t = 3.8209*** **	**t = 30.6707*** **
VaR	0.0064	0.0010	0.0100	−0.0216	0.0176	0.0114	0.0044	0.0171	0.0260
	t = 0.2869	t = 0.0913	t = 0.2747	t = −0.6953	t = 0.8303	t = 0.3801	t = 0.1508	t = 0.8066	**t = 8.8361*** **
Illiquidity	0.1834	0.1001	0.0224	0.0664	0.0853	−0.0204	0.1144	0.0905	0.0090
	t = 3.2242* **	**t = 3.2832*** **	t = 0.2549	t = 0.8668	t = 1.5880	t = −0.2798	t = 1.5570	**t = 1.6871***	t = 1.2520
N	10,732	100	10,732	10,732	10,732	10,732	10,732	10,732	10,732
Adjusted R^2	0.0080	0.7952	0.2530	0.0150	−0.0075	0.0005	0.0187	0.0028	0.0023
F Statistic	**15.5004*** **	**65.0838*** **	**18.099*** **	**44.7066*** **	**5.5486*** **	**36.2222*** **	**210.4873*** **	**36.0102*** **	**15,566.9900*** **

Notes: This model runs regressions of monthly stock returns on CAPM beta, firm size, firm value, momentum, VaR, and illiquidity from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 5.3: Model 1b

$$R_{i,t+1} = \gamma_0 + \gamma_1\beta_{i,t}^{DCC} + \gamma_2 Size_{i,t} + \gamma_3 Value_{i,t} + \gamma_4 Mom_{i,t} + \gamma_5 Illiq_{i,t} + \gamma_6 CVaR_{i,t} + \varepsilon_i$$

Models / Coefficients	OLS	BE	FM	FE Individual Effects	FE Time Effects	FE Individual & Time Effects	RE Individual Effects	RE Time Effects	RE Individual & Time Effects
Alpha	1.1473	0.2466	0.7296				0.7267	0.7914	−0.6849
	t = 3.3611* **	t = 1.4532	**t = 1.8773***				t = 1.3143	t = 1.4798	**t = −8.6152*** **
DCC Beta	0.7537	0.2262	0.5371	1.7800	0.7174	1.8653	1.5723	0.7186	1.9171
	t = 2.3752 **	**t = 1.6755***	t = 0.9208	**t = 2.6017*** **	**t = 2.4532** **	**t = 2.9448*** **	**t = 2.8466*** **	**t = 2.4582** **	**t = 33.2449*** **
Firm Size (Size)	0.2149	0.0803	−0.0898	−1.5820	−0.0445	−3.3113	−0.5392	−0.0296	−1.8527
	t = 1.6615*	t = 1.4088	t = −0.5670	**t = −5.2338*** **	t = −0.3644	**t = −9.8236*** **	**t = −2.3454** **	t = −0.2432	**t = −67.5584*** **
Firm Value (Value)	1.1871	−0.1282	0.1793	2.3111	0.3485	0.3173	2.4847	0.3961	1.0352
	t = 5.1562* **	t = −1.0704	t = 0.5661	**t = 6.2130*** **	t = 1.5819	t = 0.8417	**t = 7.5797*** **	**t = 1.8022***	**t = 29.6434*** **
Momentum	0.0111	0.0669	0.0148	0.0081	0.0091	0.0145	0.0050	0.0093	0.0082
	t = 4.4671* **	**t = 16.5769*** **	**t = 2.6741*** **	**t = 2.5079** **	**t = 3.6922*** **	**t = 4.5572*** **	**t = 1.7164***	**t = 3.7804*** **	**t = 27.5238*** **
CVaR	−0.0139	0.0025	−0.0047	−0.0627	−0.0107	−0.0212	−0.0363	−0.0109	−0.0187
	t = −0.7934	t = 0.2818	t = −0.1987	**t = −2.5602** **	t = −0.6418	t = −0.8948	t = −1.5813	t = −0.6520	t = −8.0670***
Illiquidity	0.2301	0.0955	0.0721	0.1334	0.1274	−0.0348	0.1806	0.1330	0.0171
	t = 4.0744* **	**t = 3.1758*** **	t = 0.9380	**t = 1.7999***	**t = 2.3965** **	t = −0.4901	**t = 2.5544** **	**t = 2.5065** **	**t = 2.4324** **
N	10,732	100	10,732	10,732	10,732	10,732	10,732	10,732	10,732
Adjusted R^2	0.0086	0.7942	0.2681	0.0148	−0.0070	0.0012	0.0184	0.0033	0.0027
F Statistic	**16.4414*** **	**64.6864*** **	**16.436** **	**44.4255*** **	**6.4370*** **	**37.5198*** **	**207.2984*** **	**41.4099*** **	**16,320.4100*** **

Notes: This model runs regressions of monthly stock returns on DCC beta, firm size, firm value, momentum, CVaR, and illiquidity from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

5.5. Residual Analysis

5.5.1. Normality Test

Table 5.4: The JB Test for Residuals of Different Estimations

Estimations	JB Test	Statistics	p-value
Panel A: Model (1a)			
OLS		14,015	< 2.2E-16
BE		4.5879	0.1009
FM		10,034	< 2.2E-16
FE	**Individual Effects**	13,359	< 2.2E-16
	Time Effects	15,043	< 2.2E-16
	Individual & Time Effects	14,547	< 2.2E-16
RE	**Individual Effects**	13,391	< 2.2E-16
	Time Effects	16,425	< 2.2E-16
	Individual & Time Effects	9,028.1	< 2.2E-16
Panel B: Model (1b)			
OLS		13,953	< 2.2E-16
BE		3.247	0.1972
FM		9,778.5	< 2.2E-16
FE	**Individual Effects**	13,314	< 2.2E-16
	Time Effects	15,131	< 2.2E-16
	Individual & Time Effects	14,329	< 2.2E-16
RE	**Individual Effects**	13,320	< 2.2E-16
	Time Effects	16,499	< 2.2E-16
	Individual & Time Effects	9,038	< 2.2E-16

Notes: The JB test is computed from January 2011 to December 2019 for the residuals of different estimations. The null hypothesis of the JB test is that the residuals are normally distributed.

Table 5.4 presents the results of Jarque–Bera test (JB) for the normality of residuals of all estimations from January 2011 to December 2019. Under regression estimations, the unobserved error should be normally distributed to satisfy the normality assumption that leads to the efficiency and effectiveness of statistical inferences (Wooldridge, 2012). Wooldridge

(2012) shows that the variances of coefficients are biased if the unobserved error violates this assumption. This violation leads to invalid t-statistics.

Panels A and B in Table 5.4 show the tests for residuals in models (1a) and (1b), respectively. Only the between-estimator passes the JB test in both models at a 10 per cent level. Furthermore, the residuals of the between-estimator technique in Panel B have a higher p-value than in Panel A. This means using the DCC beta and CVaR fit model better than using CAPM beta and VaR. Other estimations have p-values much below the hurdle rate 1 per cent, 5 per cent, and 10 per cent levels. Therefore, the null hypothesis that normal distributions of residuals of the other estimations are rejected. The violation of the normality assumption will reduce the statistical inference of estimated coefficients. Therefore, all coefficients should be robust to tackle this issue. The robustness is shown in Section 5.6.

Figures 5.3 and 5.4 show the Q-Q plots of residuals for models (1a) and (1b), respectively. If the residuals are normal distributions, the plots should lie on straight lines. Because the Q-Q plots in Figures 5.3 and 5.4 show that the residuals deviate significantly from the straight lines, except for the between-estimator. Therefore, the null hypothesis on the normal distribution of residuals is appropriate only for the between-estimator and it is rejected for other regressions.

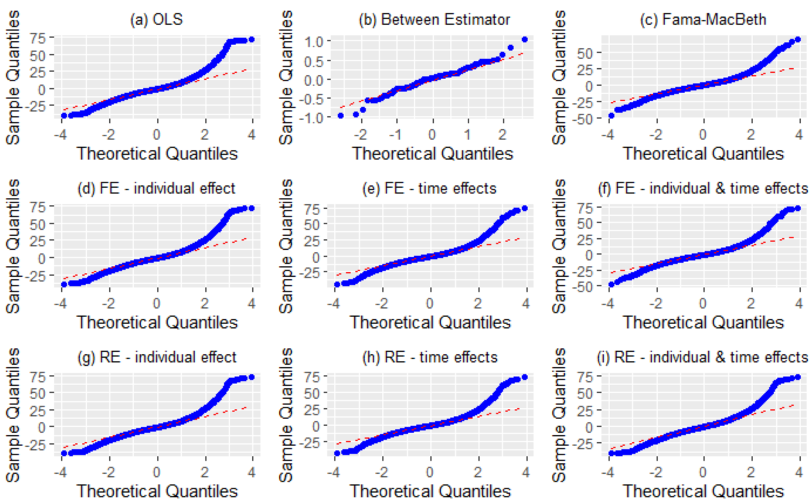


Figure 5.3: Q-Q Plots of Residuals for Model (1a)

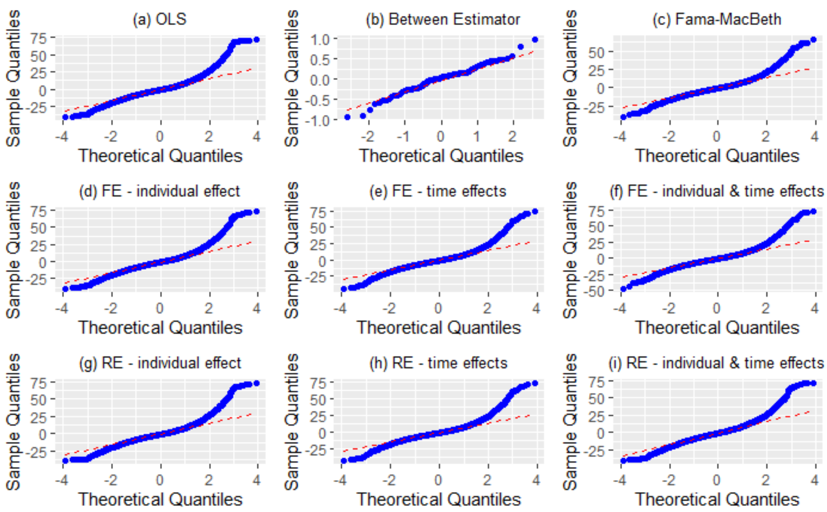


Figure 5.4: Q-Q Plots of Residuals for Model (1b)

5.5.2. Serial Correlation Test

Table 5.5 shows the Breusch–Godfrey (BG) test for the residuals of different estimations calculated from January 2011 to December 2019. If the errors of a regression model are correlated with its lags, the estimated coefficients are inconsistent (Croissant & Millo, 2018; Fama, 2014; Wooldridge, 2012).

Table 5.5: The BG Test for the Residuals of Different Estimations

Panel A: Model (1a)			
Estimations \ BG Test		Statistics	p-value
OLS		388.83	< 2.2E-16
BE		2.387	0.1223
FM		317.3	< 2.2E-16
FE	Individual Effects	468.7	< 2.2E-16
	Time Effects	136.83	0.0032
	Individual & Time Effects	168.15	5.6E-06
RE	Individual Effects	412.05	< 2.2E-16
	Time Effects	141.69	0.0013
	Individual & Time Effects	388.83	< 2.2E-16
Panel B: Model (1b)			
Estimations \ BG Test		Statistics	p-value
OLS		389.2	< 2.2E-16
BE		2.4136	0.1203
FM		317.7	< 2.2E-16

FE	**Individual Effects**	483.06	< 2.2E-16
	Time Effects	138.81	0.0023
	Individual & Time Effects	169.47	4.1E-06
RE	**Individual Effects**	411.9	< 2.2E-16
	Time Effects	143.56	0.0010
	Individual & Time Effects	389.2	< 2.2E-16

Notes: The BG test is computed from January 2011 to December 2019 for the residuals of different estimations. The null hypothesis of the BG test is that no autocorrelation in the residuals.

The Breusch–Godfrey test (BG) (see Croissant & Millo, 2018; Wooldridge, 2012) in Table 5.5 shows that no serial correlation in the error of the between-estimator technique in both models (1a) and (1b) because the p-values of the test are higher than the 10 per cent level. In contrast, this problem is detected in other estimations in both models (1a) and (1b) because the p-values of the test are smaller than the 1 per cent level. The existence of the serial correlation in the errors will reduce the statistical inference of estimated coefficients. Therefore, all coefficients should be robust to tackle this issue. The robustness is shown in Section 5.6.

5.5.3. Heteroskedasticity Test

Wooldridge (2012), Croissant and Millo (2018) show that the variance of the error in a regression model should be constant (homoscedasticity) to obtain unbiased coefficients. However, in case the variance of the error is nonconstant (heteroskedasticity), it causes biases in estimated coefficients and invalid statistical inference. The heteroskedasticity is tested using the Breusch–Pagan test (BP) for the between-estimator (cross-sectional data) (see Wooldridge, 2012) and the Pesaran CD test (PCD) for other estimations (panel data) (see Croissant & Millo, 2018). Table 5.6 shows heteroskedasticity tests for the residuals of different estimations calculated from January 2011 to December 2019.

Table 5.6 shows that only FM regression and time RE estimation cannot reject the null hypothesis (no cross-sectional dependence in the errors) because the p-values are high, approximately 15 per cent level for FM regression and 96 per cent for RE (time effects). The other estimations show the significance of the cross-sectional dependence in the errors because of low p-values. The existence of heteroskedasticity will reduce the statistical inference of estimated coefficients. Therefore, all coefficients should be robust to tackle this issue. The robustness is shown in Section 5.6.

Table 5.6: Heteroskedasticity Tests for the Residuals of Different Estimations

Panel A: Model (1a)			
Estimations \ **PCD / BP Tests**		**Statistics**	**p-value**
OLS		126.86	< 2.2E-16
BE		19.659	0.0032
FM		−1.429	0.153
FE	**Individual Effects**	124.87	< 2.2E-16
	Time Effects	−6.2119	5.2E-10
	Individual & Time Effects	−6.2301	4.7E-10
RE	**Individual Effects**	124.85	< 2.2E-16
	Time Effects	−0.0377	0.9699
	Individual & Time Effects	129.32	< 2.2E-16
Panel B: Model (1b)			
Estimations \ **PCD / BP Tests**		**Statistics**	**p-value**
OLS		126.76	< 2.2E-16
BE		17.004	0.0093
FM		−1.41	0.1585
FE	**Individual Effects**	125.8	< 2.2E-16
	Time Effects	−6.2097	5.3E-10
	Individual & Time Effects	−6.2355	4.5E-10
RE	**Individual Effects**	125.18	< 2.2E-16
	Time Effects	−0.0442	0.9647
	Individual & Time Effects	129.04	< 2.2E-16

Notes: The heteroskedasticity tests (PCD and BP) are computed from January 2011 to December 2019 for the residuals of different estimations. The null hypothesis of the heteroskedasticity tests is no cross-sectional dependence in the residuals.

5.6. Robust Standard Error (SE)

Although panel data regressions are common in finance (Fama & French, 1992; 1998; Hanauer & Lauterbach, 2019; Petersen, 2009), most papers do not report the robust standard errors of estimated coefficients for possible dependence in the residuals (Petersen, 2009). The popular approach in the literature when studying the cross-section of stock returns and their characteristics is using Fama–MacBeth regression (Fama & French, 1992; Hanauer & Lauterbach, 2019; Jagannathan & Wang, 2002; Novy-Marx, 2013; Petersen, 2009). However, Petersen (2009) explains that although standard errors from Fama–MacBeth regression account for cross-correlation, the estimations from this method will be biased if there exists a serial correlation. Furthermore, this approach is designed to deal with time effects in a data set, not individual effects. Therefore, in the presence of individual effects, the standard errors of estimated coefficients are biased. It is recognised that dependence and serial correlation are problems in panel regressions because of individual effects, or time effects or both individual and time effects in panel data will cause bias in finance applications (Fama, 2014; Millo, 2017; Petersen, 2009; Thompson, 2011).

Because the residuals of regression models explained monthly stock return and their firm characteristics on the HSX are non-normal, serial correlated, and/ (or) cross-sectional dependent, the estimated coefficients are biased. The standard errors of these betas will be inflated or deflated. Hence, to reduce the problems, standard errors of the coefficients should be robust and reported (Petersen, 2009). This thesis applies two robust techniques: the traditional technique called Newey and West (1987), and new clustering techniques (Millo, 2019; Petersen, 2009; Thompson, 2011). The randomness of the residuals of models (1a) and (1b) are shown in Figures 5.5 and 5.6. These figures show that the means of the errors of different estimations are close to zero; however, the variances of these errors may change (heteroskedasticity) because the dispersions are not random. Under the homoskedasticity assumption, the variance of the errors should be unchanged.

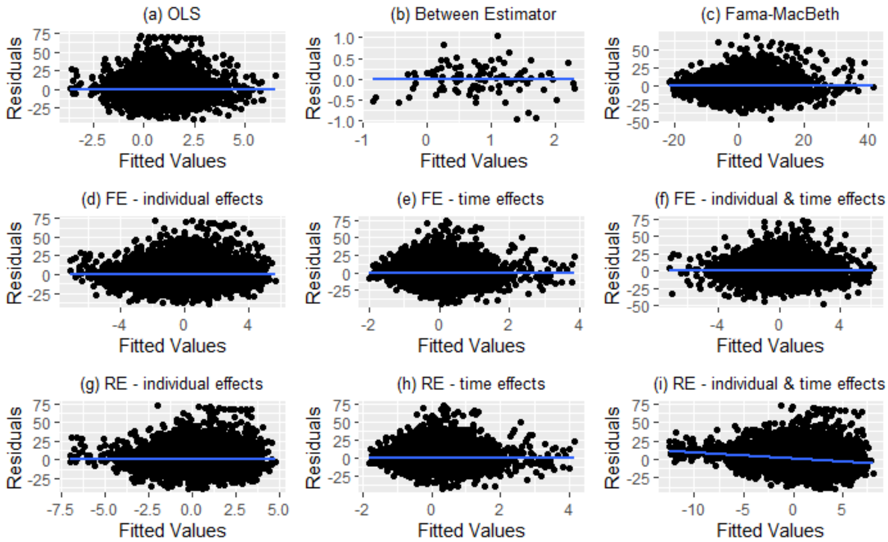


Figure 5.5: Residual Plots for Model (1a)

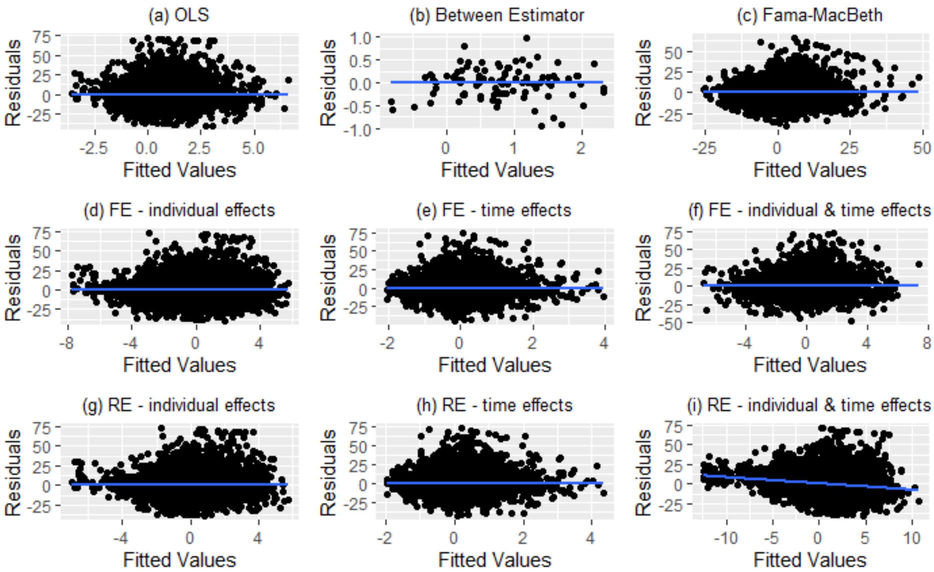


Figure 5.6: Residual Plots for Model (1b)

The following sections apply both Newey and West (1987) and different clustering techniques to robust the standard errors of estimations. The t-statistics of nonrobust and robust models are reported to understand the bias of different estimations. The numbers in parentheses show the difference in t-statistics between the nonrobust models and the robust models measured in percentage. If the numbers in the parentheses are positive, the estimated coefficients are biased upward (the t-statistics of the nonrobust model are higher than those in robust models). In contrast, if these numbers are negative, the estimated coefficients are biased downward (the t-statistics of the nonrobust model are lower than those in robust models). The details of robust tests for each estimation are as follows:

5.6.1. Robust Tests for OLS Estimation

Table 5.7 shows the robustness of the standard error using the OLS estimation from January 2011 to December 2019. This table compares the t-statistics of the nonrobust and robust models using Newey and West (1987) and clustering for OLS estimation in models (1a) and (1b) under the existence and nonexistence of individual effects, time effects, or both effects.

Both the robustness of standard errors using the method developed by Newey and West (1987) (Newey–West) and different clustering techniques show that CAPM beta is biased downward in OLS estimation. The t-statistics of CAPM beta in the nonrobust models are lower than those in the robust models from 20.7 per cent (Newey–West) to 59.3 per cent (double clustering) (see Panel A). Furthermore, OLS estimations show that CAPM beta is negatively correlated with stock returns in the HSX, but this relation is insignificant. In contrast, DCC beta is biased upward in OLS estimation. The t-statistics of DCC beta in the nonrobust models are higher than those from robust models approximately from 18.4 per cent (individual clustering) to 94.2 per cent (time clustering) (see Panel B). Moreover, DCC beta is positively correlated with stock returns in the HSX and significant at 1 per cent and 5 per cent levels after robustness using Newey and West (1987) and individual clustering, respectively. However, the time clustering and double clustering show that DCC beta is statistically insignificant in OLS regression.

Table 5.7: Robustness for OLS Estimation

Models / Coefficients	Nonrobustness	Robustness			
		Newey–West	Individual Clustering	Time Clustering	Double Clustering
Panel A: Model (1a)					
CAPM Beta	−0.0526	−0.0417	−0.0407	−0.0217	−0.0214
		[−20.7%]	[−22.6%]	[−58.7%]	[−59.3%]
Firm Size	**1.9174***	**1.7740***	1.62	1.2152	1.1584
		[8.1%]	[18.4%]	[57.8%]	[65.5%]
Firm Value	**5.6180*****	**4.9089*****	**5.3308*****	**2.6443*****	**2.6759*****
		[14.4%]	[5.4%]	[112.5%]	[109.9%]
Momentum	**4.4195*****	**3.6251*****	**4.4328*****	**1.7118***	**1.7633***
		[21.9%]	[−0.3%]	[158.2%]	150.6%
VaR	0.2869	0.2146	0.2401	0.156	0.166
		[33.7%]	[19.5%]	[83.9%]	[72.8%]
Illiquidity	**3.2242*****	**2.8983*****	**2.6862*****	**2.0415****	**1.9707****
		[11.2%]	[20.0%]	[57.9%]	[63.6%]

Notes: Numbers in the parentheses show the bias of t-statistics in the OLS models compared to the robustness using the method developed by Newey and West (1987), individual clustering, time clustering, and double clustering. If these numbers are positive, t-statistics in this estimation are biased upward. Otherwise, t-statistics using this model are biased downward. Data is from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Firm size is biased upward using OLS estimation. The t-statistic of this variable in the nonrobust model is higher than those in the robust models approximately from 8.1 per cent (Newey–West) to 65.5 percent (double clustering) in model (1a) (see Panel A), and approximately from 8.4 per cent (Newey–West) to 83.9 per cent (double clustering) in model (1b) (see Panel B). Firm size is positively correlated with stock returns in the HSX in OLS estimation. However, the effect of firm size is significant on stock return in the HSX only in model (1a) after robustness using Newey and West (1987). Clustering techniques show that firm size is statistically insignificant.

Firm value is also biased upward using OLS estimation. The t-statistic of this variable in the nonrobust model is higher than those in the robust models approximately from 5.4 per cent (individual clustering) to 112.5 per cent (time clustering) in model (1a) (see Panel A), and approximately from 4 per cent to 105.2 per cent (time clustering) in model (1b) (see Panel B). Firm value is positively correlated with stock returns in the HSX in OLS estimation. In addition, the effect of firm value is significant on stock return in the HSX from 1 per cent to 5 per cent levels in both models (1a) and (1b) under different robustness in both Panels A and B.

While individual clustering shows that momentum is biased downward, other robust techniques show that momentum is biased upward in both models (1a) (Panel A) and (1b) (Panel B) under OLS estimation. The t-statistics of momentum in the nonrobust models are lower than those in robust models using individual clustering approximately 0.3 per cent in model (1a) (Panel A) and 3.5 per cent in model (1b) (Panel B). In contrast, the t-statistic in the nonrobust model is higher than those in the robust models using other robust techniques approximately from 21.9 per cent to 158.2 per cent in model (1a) (Panel A), and approximately from 22.4 per cent to 164.5 per cent in model (1b) (Panel B). Momentum is positively correlated with stock returns in the HSX and is significant from 1 per cent to 10 per cent levels in OLS estimation under different robustness in both Panels A and B.

While Value-at-Risk (VaR) is biased upward in model (1a) (Panel A), conditional Value-at-Risk (CVaR) is biased downward in model (1b) (Panel B) under OLS estimation. The t-statistic of VaR in the nonrobust model is higher than those in the robust models approximately from 19.5 per cent (individual clustering) to 83.9 per cent (time clustering) (see Panel A). In contrast, the t-statistic of CVaR in the nonrobust model is lower than those in the robust models approximately from 13 per cent (individual clustering) to 47.2 per cent (time clustering) (see Panel B). While VaR is positively correlated with stock returns in the HSX, CVaR is negatively correlated with stock returns under OLS estimation in both Panels A and B. However, after robustness, VaR and CVaR are statistically insignificant on stock returns.

Illiquidity is biased upward using OLS estimation. The t-statistic in the nonrobust model is higher than those in the robust models approximately from 11.2 per cent (Newey–West) to 63.6 per cent (double clustering) in model (1a) (see Panel A), and approximately from 13 per cent (Newey–West) to 67.4 per cent (time clustering) in model (1b) (see Panel B). Illiquidity is positively correlated with stock returns in the HSX in OLS estimation. In addition, the illiquidity is significant on stock return in the HSX from 1 per cent to 5 per cent levels in both models (1a) and (1b) under different robustness in both Panels A and B.

5.6.2. Robust Tests for BE and FM Estimations

Table 5.8 shows the robustness of the standard error using BE and FM estimations from January 2011 to December 2019. This table compares the t-statistics of the non-robustness and robustness using Newey and West (1987) for BE and FM estimations in models (1a) and (1b).

Table 5.8: Robustness for BE and FM Estimations

Models / Coefficients	**BE**		**FM**	
	Nonrobustness	**Robustness (Newey–West)**	**Nonrobustness**	**Robustness (Newey–West)**
Panel A: Model (1a)				
CAPM Beta	**1.8406***	1.4958	−0.1527	−0.6941
		[23.1%]		[354.6%]
Firm Size	1.5437	1.5647	−0.6084	−0.6467
		[−1.3%]		[6.3%]
Firm Value	−1.0423	−1.3243	0.9238	0.8623
		[27.1%]		[7.1%]
Momentum	**17.0077*****	**16.1860*****	**2.9350*****	**3.4068*****
		[5.1%]		[−13.8%]
VaR	0.0913	0.0739	0.2747	0.291
		[23.5%]		[−5.6%]
Illiquidity	**3.2832*****	**2.9633*****	0.2549	0.3266
		[10.8%]		[−22.0%]
Panel B: Model (1b)				
DCC Beta	**1.6755***	1.5296	0.9208	0.9532

		[9.5%]		[−3.4%]
Firm Size	1.4088	1.4816	−0.567	−0.6224
		[−4.9%]		[9.8%]
Firm Value	−1.0704	−1.2681	0.5661	0.5424
		[18.5%]		[4.4%]
Momentum	**16.5769*** **	**15.1552*** **	**2.6741*** **	**3.6451*** **
		[9.4%]		[−26.6%]
CVaR	0.2818	0.2649	−0.1987	−0.2113
		[6.4%]		[6.3%]
Illiquidity	**3.1758*** **	**3.0964*** **	0.938	0.9588
		[2.6%]		[−2.2%]

Notes: Numbers in the parentheses show the bias of t-statistics in BE and FM models compared to the robustness using the method developed by Newey and West (1987). If these numbers are positive, t-statistics in these estimations are biased upward. Otherwise, t-statistics in both models are biased downward. Data is from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

The robustness shows that CAPM beta is biased upward in both BE and FM estimations (see Panel A). The t-statistics of CAPM beta in the nonrobust models are lower than those in the robust models approximately 23.1 per cent and 354.6 per cent for BE and FM estimations, respectively. While BE estimation shows that CAPM beta is positively correlated with stock returns in the HSX, FM estimation indicates that this relation is negative. However, CAPM beta is statistically insignificant after robustness in both estimations. While DCC beta is biased upward under BE estimation, it is biased downward under FM estimation (see Panel B). The t-statistic of DCC beta in the nonrobust model using BE estimation is higher than that in the robust model approximately 9.5 per cent. However, the t-statistic of DCC beta in the nonrobust model using FM estimation is lower than that in the robust model approximately 3.4 per cent. Although DCC beta is positively correlated with stock returns in the HSX, it is statistically insignificant after robustness in both BE and FM estimations.

While firm size is biased downward in BE estimation, it is upwardly biased in FM estimation in both models (1a) and (1b). For BE estimation, the t-statistics of firm size in the nonrobust models are lower than those in the robust models approximately 1.3 per cent in model (1a) (Panel A) and 4.9 per cent in model (1b) (Panel B). In contrast, for FM estimation, the t-statistics of this variable in the nonrobust models are higher than those in the robust models approximately 6.3 per cent in model (1a) (Panel A) and 9.8 per cent in model (1b) (Panel B). Firm size is positively correlated with stock returns in the HSX using BE estimation. However, FM estimation shows that firm size is negatively correlated with stock returns. After robustness, the effect of firm size on stock returns is not statistically significant in both models and estimations.

Firm value is biased upward in both BE and FM estimations. The t-statistics of this variable in the nonrobust models using BE estimation are higher than those in robust models in both models (1a) and (1b) approximately from 18.5 per cent (Panel B) to 27.1 per cent (Panel A). Similarly, the t-statistics of firm value in the nonrobust models using FM estimation are higher than those in robust models and approximately from 4.4 per cent (Panel B) to 7.1 per cent (Panel A). While BE estimation shows that value is negatively correlated with stock returns in the HSX, FM estimation indicates that this relation is negative. After robustness, the effect of firm value on stock returns is not statistically significant in both models and estimations.

While momentum is biased upward in BE estimation, it is biased downward in FM estimation in both models (1a) and (1b). For BE estimation, the t-statistics of momentum in the nonrobust models are higher than those in the robust models approximately 5.1 per cent in model (1a) (Panel A) and 9.4 per cent in model (1b) (Panel B). In contrast, for FM estimation, the t-statistics of this variable in the nonrobust models are lower than those in the robust models approximately 13.8 per cent in model (1a) (Panel A) and 26.6 per cent in model (1b) (Panel B). Momentum is positively correlated with stock returns in the HSX in both models (1a) and (1b) and both BE and FM estimations. After robustness, the momentum effect on stock returns is statistically significant at a 1 per cent level in both models and estimations.

While Value-at-Risk (VaR) in model (1a) (Panel A) is biased upward in BE estimation, it is biased downward in FM estimation. For BE estimation, the t-statistic of VaR in the nonrobust model is higher than that in the robust model approximately 23.5 per cent. In contrast, for FM estimation, the t-statistic of this variable in the nonrobust model is lower than that in the robust model approximately 5.6 per cent. VaR is positively correlated with stock returns in the HSX in both BE and FM estimations. However, after robustness, the effect of VaR on stock returns is statistically insignificant in both estimations. Conditional Value-at-Risk (CVaR) in model (1b) (Panel B) is biased upward in both BE and FM estimations. The t-statistics of this variable in the nonrobust models are higher than those in robust models approximately 6.4 per cent and 6.3 per cent for BE and FM estimations, respectively. While BE estimation shows that CVaR is positively correlated with stock returns in the HSX, FM estimation indicates that this relation is negative. After robustness, the effect of CVaR on stock returns is statistically insignificant in both estimations.

While illiquidity is biased upward in BE estimation, it is biased downward in FM estimation in both models (1a) and (1b). For BE estimation, the t-statistics of illiquidity in the nonrobust models are higher than those in the robust models approximately 10.8 per cent in model (1a) (Panel A) and 2.6 per cent in model (1b) (Panel B). In contrast, for FM estimation, the t-statistics of this variable in the nonrobust models are lower than those in the robust models approximately 22 per cent in model (1a) (Panel A) and 2.2 per cent in model (1b) (Panel B). Illiquidity is positively correlated with stock returns in the HSX in both models (1a) and (1b) and both BE and FM estimations. After robustness, the effect of illiquidity on stock returns is only statistically significant in BE estimation at a 1 percent level for both models.

5.6.3. Robustness for FE and RE Estimations

5.6.3.1. Individual Effects

Table 5.9 shows the robustness of the standard error using the FE and RE estimations from January 2011 to December 2019 under the existence of individual effects. This table compares the t-statistics of the non-robustness and robustness using Newey and West (1987) and individual clustering for models (1a) and (1b).

Table 5.9: Robustness for FE and RE Estimations under Individual Effect

Models / Coefficients	FE			RE		
	Nonrobustness	Robustness		Nonrobustness	Robustness	
		Newey–West	Individual Clustering		Newey–West	Individual Clustering
Panel A: Model (1a)						
CAPM Beta	**−3.0275*** **	**−2.5389** **	**−2.1409** **	**−1.9185***	−1.5576	−1.4005
		[−16.1%]	[−29.3%]		[−18.8%]	[−27.0%]
Firm Size	**−5.6275*** **	**−4.4966*** **	**−3.6245*** **	**−2.5083** **	**−2.2457** **	**−2.0448** **
		[−20.1%]	[−35.6%]		[−10.5%]	[−18.5%]
Firm Value	**6.1268*** **	**4.6373*** **	**3.6929*** **	**7.9394*** **	**6.2153*** **	**5.3563*** **
		[32.1%]	[65.9%]		[27.7%]	[48.2%]
Momentum	**3.0440*** **	**2.4054** **	**2.0338** **	**1.8135***	1.4445	1.3299
		[26.5%]	[49.7%]		[25.5%]	[36.4%]
VaR	−0.6953	−0.5495	−0.4943	0.1508	0.1168	0.1163
		[−21.0%]	[−28.9%]		[29.1%]	[29.7%]
Illiquidity	0.8668	0.7933	0.802	1.557	1.4364	1.4483
		[9.3%]	[8.1%]		[8.4%]	[7.5%]
Panel B: Model (1b)						
DCC Beta	**2.6017*** **	**2.1424** **	**1.8175***	**2.8466*** **	**2.2904** **	**2.2348** **
		[21.4%]	[43.1%]		[24.3%]	[27.4%]
Size	**−5.2338*** **	**−4.0834*** **	**−3.4695*** **	**−2.3454** **	**−2.0690** **	**−1.8233***
		[−22.0%]	[−33.7%]		[−11.8%]	[−22.3%]
Value	**6.2130*** **	**4.6665*** **	**3.5959*** **	**7.5797*** **	**5.9558*** **	**4.9688*** **
		[33.1%]	[72.8%]		[27.3%]	[52.5%]
Momentum	**2.5079** **	**1.9945** **	**1.8279***	**1.7164***	1.3734	1.3636
		[25.7%]	[37.2%]		[25.0%]	[25.9%]
CVaR	**−2.5602** **	**−2.1892** **	**−1.7979***	−1.5813	−1.3526	−1.2217

		[−14.5%]	[−29.8%]		[−14.5%]	[−22.7%]
Illiquidity	**1.7999***	1.6264	1.6134	**2.5544****	**2.3184****	**2.4473****
		[10.7%]	[11.6%]		[10.2%]	[4.4%]

Notes: Numbers in the parentheses show the bias of t-statistics in the FE (individual effect) and RE (individual effect) models compared to the robustness using the method developed by Newey and West (1987) and individual clustering. If these numbers are positive, t-statistics in these estimations are biased upward. Otherwise, t-statistics in these models are biased downward. Data is from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Both the robustness of standard errors using the method developed by Newey and West (1987) and individual clustering show that CAPM beta is biased downward in both FE and RE estimations. In Panel A, the t-statistics of CAPM beta in the nonrobust models are lower than those in the robust models from 16.1 per cent (Newey–West) to 29.3 per cent (individual clustering) for FE estimation, and approximately from 18.8 per cent (Newey–West) to 27 per cent (individual clustering) for RE estimation. Furthermore, under the individual effects, both FE and RE estimations show that CAPM beta is negatively correlated with stock returns in the HSX, but this relation is significant only in FE estimation after robustness at a 5 per cent level. In contrast, DCC beta is biased upward in both FE and RE estimations. In Panel B, the t-statistics of DCC beta in the nonrobust models are higher than those in robust models approximately from 21.4 per cent (Newey–West) to 43.1 per cent (individual clustering) for FE estimation, and approximately from 24.3 per cent (Newey–West) to 27.4 per cent (Individual Clustering) for RE estimation. Moreover, DCC beta is positively correlated with stock returns in the HSX and significant from 5 per cent to 10 per cent levels in both FE and RE models after robustness.

Both the robustness of standard errors using the method developed by Newey and West (1987) and individual clustering show that firm size is biased downward in both models and both FE and RE estimations. The t-statistics of firm size in the nonrobust models are lower than those in robust models in both models (1a) and (1b) approximately from 20.1 per cent to 35.6 per cent for FE estimation, and approximately from 10.5 per cent to 22.3 per cent for RE estimation. Firm size is negatively correlated with stock returns in the HSX and significant from 1 per cent to 10 per cent level in both FE and RE estimations and both models (1a) and (1b) after robustness.

Both the robustness of standard errors using the method developed by Newey and West (1987) and individual clustering show that firm value is biased upward in both FE and RE estimations. The t-statistics of this variable in the nonrobust models are higher than those in robust models in both models (1a) and (1b) approximately from 32.1 per cent to 72.8 per cent for FE estimation, and approximately from 27.3 per cent to 52.5 per cent for RE estimation. Firm value is positively correlated with stock returns in the HSX and significant at a 1 per cent level in both FE and RE estimations and in both models (1a) and (1b) after robustness.

Both the robustness of standard errors using the method developed by Newey and West (1987) and individual clustering show that momentum is biased upward in both FE and RE estimations. The t-statistics of momentum in the nonrobust models are higher than those in robust models in both models (1a) and (1b) approximately from 25.7 per cent to 49.7 per cent for FE estimation, and approximately from 25 per cent to 36.4 per cent for RE estimation. Momentum is positively correlated with stock returns in the HSX; however, it is significant from 5 per cent to 10 per cent levels only in FE estimation and in both models (1a) and (1b) after robustness.

Value-at-Risk (VaR) is biased downward in FE estimation but biased upward in RE estimation. The t-statistic of VaR in the nonrobust model is lower than those in the robust models approximately from 21 per cent to 28.9 per cent for FE estimation. In contrast, the RE estimation shows that the t-statistic of VaR in the nonrobust model is higher than those in the robust models approximately from 29.1 per cent to 29.7 per cent. While FE estimation indicates that VaR is negatively correlated with stock returns in the HSX, RE estimation shows that this relation is positive. However, VaR is statistically insignificant in both FE and RE estimations after robustness. Conditional Value-at-Risk (CVaR) is biased downward in both FE and RE estimations. The t-statistic of CVaR in the nonrobust model is lower than those in the robust models approximately from 14.5 per cent to 29.8 per cent for FE estimation, and approximately from 14.5 per cent to 22.7 per cent for RE estimation. CVaR is negatively correlated with stock returns in the HSX in both FE and RE estimations. However, CVaR is statistically significant only in FE estimation from 5 per cent to 10 per cent levels after robustness.

Illiquidity is biased upward in both FE and RE estimations. The t-statistics of illiquidity in the nonrobust models are higher than those in robust models in both models (1a) and (1b) approximately from 8.1 per cent to 11.6 per cent for FE estimation, and approximately from 4.4 per cent to 10.2 per cent for RE estimation. Illiquidity is positively correlated with stock returns in the HSX in both FE and RE estimations and under individual effects; however, it is significant at a 5 per cent level only in RE estimation in model (1b) after robustness.

5.6.3.2. Time Effects

Table 5.10 shows the robustness of the standard error using the FE and RE estimations from January 2011 to December 2019 under the existence of time effects. This table compares the t-statistics of the non-robustness and robustness using Newey and West (1987) and time clustering for models (1a) and (1b).

Table 5.10: Robustness for FE and RE Estimations under Time Effects

Models / Coefficients	FE			RE		
	Nonrobustness	Robustness		Nonrobustness	Robustness	
		Newey–West	Time Clustering		Newey-West	Time Clustering
Panel A: Model (1a)						
CAPM Beta	−0.0853	−0.0696	−0.0638	−0.0975	−0.0784	−0.0728

Models / Coefficients	FE			RE		
	Nonrobustness	Robustness		Nonrobustness	Robustness	
		Newey–West	Time Clustering		Newey-West	Time Clustering
		[−18.4%]	[−25.2%]		[−19.6%]	[−25.3%]
Firm Size	−0.0299	−0.028	−0.0273	0.0883	0.0824	0.0798
		[−6.4%]	[−8.7%]		[7.2%]	[10.7%]
Firm Value	**1.9787****	**1.8232***	**2.2399****	**2.2048****	**1.9967****	**2.4307****
		[8.5%]	[−11.7%]		[10.4%]	[−9.3%]
Momentum	**3.7377*****	**2.9863*****	**3.0421*****	**3.8209*****	**3.0363*****	**3.2026*****
		[25.2%]	[22.9%]		[25.8%]	[19.3%]
VaR	0.8303	0.6068	0.6703	0.8066	0.5874	0.6565
		[36.8%]	[23.9%]		[37.3%]	[22.9%]
Illiquidity	1.588	1.3898	1.4064	1.6871*	1.4742	1.469
		[14.3%]	[12.9%]		[14.4%]	[14.8%]
Panel B: Model (1b)						
DCC Beta	**2.4532****	**2.0369****	**2.1473****	**2.4582****	**2.0249****	**2.1182****
		[20.4%]	[14.2%]		[21.4%]	[16.1%]
Firm Size	−0.3644	−0.3436	−0.3326	−0.2432	−0.2281	−0.2199
		[−5.7%]	[−8.7%]		[−6.2%]	[−9.6%]
Firm Value	1.5819	1.4538	**1.7807***	**1.8022***	1.6286	**1.9878****
		[8.8%]	[−11.2%]		[10.7%]	[−9.3%]
Momentum	**3.6922*****	**2.9489*****	**3.0597*****	**3.7804*****	**3.0017*****	**3.2371*****
		[25.2%]	[20.7%]		[25.9%]	[16.8%]
CVaR	−0.6418	−0.5	−0.523	−0.652	−0.5082	−0.5349
		[−22.1%]	[−18.5%]		[−22.1%]	[−18.0%]
Illiquidity	**2.3965****	**2.0628****	**2.1991****	**2.5065****	**2.1561****	**2.2564****
		[16.2%]	[9.0%]		[16.3%]	[11.1%]

Notes: Numbers in the parentheses show the bias of t-statistics in FE (time effect) and RE (time effect) models compared to the robustness using the method developed by Newey and West (1987) and time clustering. If these numbers are positive, t-statistics in these estimations are biased upward. Otherwise, t-statistics in these models are biased downward. Data is from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Both the robustness of standard errors using the method developed by Newey and West (1987) and time clustering show that CAPM beta is biased downward in both FE and RE estimations. The t-statistics of CAPM beta in the nonrobust models are lower than those in the robust models from 18.4 per cent to 25.2 per cent for FE estimation, and approximately from 19.6 per cent to 25.3 per cent for RE estimation. Furthermore, under the time effects, both FE and RE estimations show that CAPM beta is negatively correlated with stock returns in the HSX, but this relation is insignificant. In contrast, DCC beta is biased upward in both FE and RE estimations. The t-statistics of DCC beta in the nonrobust models are higher than those in robust models approximately from 14.2 per cent to 20.4 per cent for FE estimation, and approximately from 16.1 per cent to 21.4 per cent for RE estimation. Moreover, DCC beta is positively correlated with stock returns in the HSX and significant at a 5 per cent level in both FE and RE models.

In Panel A, firm size is biased downward using FE estimation and is biased upward using RE estimation. In Panel B, this variable is biased downward in both FE and RE estimations. In model (1a) (Panel A), the t-statistic in the nonrobust model is lower than those in the robust models approximately from 6.4 per cent to 8.7 per cent for FE estimation. However, this number in the nonrobust model is higher than those in the robust models approximately from 7.2 per cent to 10.7 per cent for RE estimation. In model (1b) (Panel B), the t-statistics of firm size in the nonrobust model are lower than those in the robust models approximately from 5.7 per cent to 8.7 per cent for FE estimation, and approximately from 6.2 per cent to 9.6 per cent for RE estimation. In model (1a), firm size is negatively correlated with stock returns in the HSX for FE estimation but positively correlated with stock returns for RE estimation. In model (1b), size is negatively correlated with monthly stock returns in both FE and RE estimations. However, the effect of firm size is insignificant on stock return in the HSX for all estimations in both models.

While the robustness using Newey and West (1987) shows that firm value is biased upward, time clustering shows that this variable is biased downward. The t-statistics in the nonrobust model are higher than those in the robust model using Newey and West (1987) in both models approximately 9 per cent and 11 per cent for FE and RE estimations, respectively. However, these numbers in the nonrobust models are lower than those in robust models using time clustering in both models approximately 12 per cent and 9 per cent for FE and RE estimations, respectively. In model (1a), firm value is positively correlated with stock returns in both FE and RE estimations from 5 per cent to 10 per cent levels after robustness using both Newey and West (1987) and time clustering. In model (1b), the positive correlation between firm value and stock returns is only found in both FE and RE estimations after robustness using time clustering.

Both the robustness of standard errors using the method developed by Newey and West (1987) and time clustering show that momentum is biased upward in both FE and RE estimations. The t-statistics of momentum in the nonrobust models are higher than in robust models in both models (1a) and (1b) approximately from 20.7 per cent to 25.2 per cent for FE estimation, and approximately from 16.8 per cent to 25.9 per cent for RE estimation. Momentum is positively correlated with stock returns in the HSX and significant at a 1 percent level in both FE and RE estimations and in both models (1a) and (1b).

While Value-at-Risk (VaR) is biased upward in both FE and RE estimations (Panel A), conditional Value-at-Risk (CVaR) is biased downward in both FE and RE estimations (Panel B). The t-statistics of VaR in the nonrobust models are higher than in the robust models approximately from 23.9 per cent to 36.8 per cent for FE estimation, and approximately from 22.9 per cent to 37.3 per cent for RE estimation. In contrast, the t-statistics of CVaR in the nonrobust models are lower than in the robust models approximately from 18.5 per cent to 22.1 per cent for FE estimation, and approximately from 18 per cent to 22.1 per cent for RE estimation. While VaR is positively correlated with stock returns in the HSX, CVaR is negatively correlated with stock returns. However, FE and RE estimations show that both VaR and CVaR are statistically insignificant after robustness.

Both the robustness of standard errors using the method developed by Newey and West (1987) and time clustering show that illiquidity is biased upward in both FE and RE estimations and both models (1a) and (1b). The t-statistics of illiquidity in the nonrobust models are higher than those in robust models in both models (1a) and (1b) approximately from 9 per cent to 16.2 per cent for FE estimation, and approximately from 11.1 per cent to 16.3 per cent for RE estimation. After robustness, although illiquidity is positively correlated with stock returns in the HSX, it is statistically insignificant in model (1a). In contrast, both robust methods show that illiquidity is positively correlated with stock returns and significant at a 5 per cent level in both FE and RE estimations in model (1b).

5.6.3.3. Both Individual and Time Effects

Table 5.11 shows the robustness of the standard error using the FE and RE estimations from January 2011 to December 2019 under the existence of both individual and time effects. This table compares the t-statistics of the non-robustness and robustness using Newey and West (1987) and double clustering for FE and RE estimations for models (1a) and (1b).

Table 5.11: Robustness for FE and RE Estimations under Both Individual and Time Effects

Models / Coefficients	FE			RE		
	Nonrobust-ness	Robustness		Nonrobustness	Robustness	
		Newey–West	Double Clustering		Newey-West	Double Clustering
Panel A: Model (1a)						
CAPM Beta	0.8422	0.7029	0.5992	0.3702	0.0357	0.0169
		[19.8%]	[40.6%]		[937.0%]	[2190.5%]
Firm Size	**−9.5126*** **	**−6.9700*** **	**−4.9041*** **	**−62.9246*** **	**−10.4829*** **	**−3.4460*** **
		[−26.7%]	[−48.4%]		[−83.3%]	[−94.5%]

Firm Value	0.8136	0.6253	0.56	**31.8782*** **	**3.9702*** **	**1.6509***
		[30.1%]	[45.3%]		[702.9%]	[1831.0%]
Momentum	**5.0347*** **	**3.8544*** **	**2.7197*** **	**30.6707*** **	**2.9061*** **	1.3806
		[30.6%]	[85.1%]		[955.4%]	[2121.5%]
VaR	0.3801	0.2996	0.2659	**8.8361*** **	0.8486	0.5617
		[26.9%]	[42.9%]		[941.3%]	[1473.1%]
Illiquidity	−0.2798	−0.251	−0.2021	1.252	0.1333	0.0711
		[−10.3%]	[−27.8%]		[839.2%]	[1660.9%]
Panel B: Model (1b)						
DCC Beta	**2.9448*** **	**2.7774*** **	**1.6633***	**33.2449*** **	**4.6890*** **	**2.3146** **
		[6.0%]	[77.0%]		[609.0%]	[1336.3%]
Firm Size	**−9.8236*** **	**−7.2636*** **	**−5.0348*** **	**−67.5584*** **	**−11.1036*** **	**−3.5911*** **
		[−26.1%]	[−48.7%]		[−83.6%]	[−67.7%]
Firm Value	0.8417	0.6521	0.5705	**29.6434*** **	**3.6651*** **	1.5973
		[29.1%]	[47.5%]		[708.8%]	[1755.8%]
Momentum	**4.5572*** **	**3.5350*** **	**2.4998** **	**27.5238*** **	**2.6009*** **	1.2305
		[28.9%]	[82.3%]		[958.2%]	[2136.8%]
CVaR	−0.8948	−0.7866	−0.6339	**−8.0670*** **	−0.8319	−0.4694
		[−12.1%]	[−29.2%]		[−89.7%]	[−94.2%]
Illiquidity	−0.4901	−0.4335	−0.3381	**2.4324** **	0.251	0.1366
		[−11.5%]	[−31.0%]		[869.1%]	[1680.7%]

Notes: Numbers in the parentheses show the bias of t-statistics in FE (both effects) and RE (both effects) models compared to the robustness using the method developed by Newey and West (1987) and double clustering. If these numbers are positive, t-statistics in these estimations are biased upward. Otherwise, t-statistics in these models are biased downward. Data is from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Both the robustness of standard errors using the method developed by Newey and West (1987) and double clustering show that CAPM beta and DCC beta are biased upward in both FE and RE estimations. The t-statistics of CAPM beta in the nonrobust models are higher than those in the robust models from 19.8 per cent to 40.6 per cent for FE estimation, and approximately from 937 per cent to 2,190 per cent for RE estimation (Panel A). Also, the t-statistics of DCC beta in the nonrobust models are higher than those in the robust models approximately from 6 per cent to 77 per cent for FE estimation, and approximately from 609 per cent to 1,336.3 per cent for RE estimation (Panel B). Under individual and time effects, both FE and RE estimations show that CAPM beta is positively correlated with stock returns in the HSX, but this relation is insignificant. After robustness, DCC beta is significant from 1 per cent to 10 per cent level in both FE and RE estimations.

Both the robustness of standard errors using the method developed by Newey and West (1987) and double clustering show that firm size is biased downward in both FE and RE estimations and both models (1a) and (1b). The t-statistics of firm size in the nonrobust models are lower than those in robust models in both models (1a) and (1b) approximately from 26.1 per cent to 48.7 per cent for FE estimation, and approximately from 67.7 per cent to 94.5 per cent for RE estimation. After robustness, firm size is negatively correlated with stock returns in the HSX and significant at a 1 per cent level in both FE and RE estimations and in both models (1a) and (1b).

In contrast to firm size, both the robustness of standard errors using the method developed by Newey and West (1987) and double clustering show that firm value is biased upward in both FE and RE estimations and both models (1a) and (1b). The t-statistics of this variable in the nonrobust models are higher than those in robust models in both models (1a) and (1b) approximately from 29.1 per cent to 47.5 per cent for FE estimation, and approximately from 702.9 per cent to 1,831 per cent for RE estimation. Firm value is positively and significantly correlated with stock returns in the HSX only in RE estimation. In model (1a), after robustness, the firm value is significant at a 1 per cent level using the method developed by Newey and West (1987) and at a 10 per cent level using double clustering. In model (1b), this variable is significant at a 1 per cent level using the method developed by Newey and West (1987).

Both the robustness of standard errors using the method developed by Newey and West (1987) and double clustering show that momentum is biased upward in both FE and RE estimations and both models (1a) and (1b). The t-statistics of this variable in the nonrobust models are higher than those in robust models in both models (1a) and (1b) approximately from 28.9 per cent to 85.1 per cent for FE estimation, and approximately from 955.4 per cent to 2,136.8 per cent for RE estimation. Momentum is positively correlated with stock returns in the HSX. In both models (1a) and (1b), after robustness, the FE estimation shows that momentum is significant from 1 per cent to 5 per cent levels. However, the RE estimation shows that this variable is only significant at a 1 per cent level after robustness using the method developed by Newey and West (1987).

While Value-at-Risk (VaR) is biased upward in both FE and RE estimations (Panel A), conditional Value-at-Risk (CVaR) is biased downward (Panel B). The t-statistics of VaR in the nonrobust models are higher than those in the robust models approximately from 26.9 per cent to 42.9 per cent for FE estimation, and approximately from 941.3 per cent to 1,473.1 per cent for RE estimation. In contrast, the t-statistics of CVaR in the nonrobust models are lower than those in the robust models approximately from 12.1 per cent to 29.2 per cent for FE estimation, and approximately from 89.7 per cent to 94.2 per cent for RE estimation. While VaR is positively correlated with stock returns in the HSX, CVaR is negatively correlated with stock returns. However, FE and RE estimations show that both VaR and CVaR are statistically insignificant under both individual and time effects.

While illiquidity is biased downward in FE estimation, this variable is biased upward in RE estimation. The t-statistics of illiquidity in the nonrobust models are lower than those in the robust models approximately from 10.3 per cent to 31 per cent for FE estimation in both models (1a) and (1b). In contrast, these statistics in the nonrobust models are higher than those in the robust models approximately from 839.2 per cent to 1,680.7 per cent for RE estimation in both models. While illiquidity is negatively correlated with stock returns in the HSX using FE estimation, it is positively correlated with stock returns using RE estimation. However, after robustness, both FE and RE estimations show that illiquidity is statistically insignificant under both individual and time effects.

5.7. Fixed Effects, Random Effects and Correlated Effects

Different estimations show different results. This section tests the correlated effects and shows the appropriate model for the HSX. To select between fixed effects and random effects, the Hausman tests are used (Croissant & Millo, 2018). Furthermore, to test for the correlated effects (individual effects, time effects, or both effects) in the error, F tests are applied (Croissant & Millo, 2018).

5.7.1. Fixed or Random Effects

Table 5.12 shows the Hausman test for panel regressions in models (1a) and (1b) for individual effects, time effects, and both individual and time effects from January 2011 to December 2019. Table 5.12 reject the null hypothesis that random effects have existed at a 5 per cent level in both models (1a) and (1b). Therefore, fixed effects are preferable.

Table 5.12: Hausman Test

Model \ Hausman Test	Effects	Chi-squared	p-value
(1a)	**Individual**	60.613	3.378E-11
(1b)		63	1.104E-11
(1a)	**Time**	21.465	0.0015
(1b)		15.267	0.0183
(1a)	**Individual & Time**	23.333	0.0007
(1b)		22.52	0.0009

Notes: The Hausman test is computed from January 2011 to December 2019 for different effects. The null hypothesis of the Hausman test is that the random effect is preferred to the fixed effect.

5.7.2. Correlated Effects

5.7.2.1. Individual Effects

Table 5.13 shows the F test to examine the existence of individual effects or no effects in the errors for both models (1a) and (1b) from January 2011 to December 2019. All values of the p-value of the F test in Table 5.13 are less than the 5 per cent level in both models (1a) and (1b). Therefore, the null hypothesis that the absence of individual effects is strongly rejected in both models. This implies that the individual effects that exist in the error and fixed effects (FE) are preferred to the OLS regression for both models.

Table 5.13: Testing Individual Effects

F Test / Model	F	p-value
(1a)	2.3126	4.033E-12
(1b)	2.2384	3.196E-11

Notes: The null hypothesis of the F test is that the individual effect is absent in the error. This test compares FE (individual effect) and OLS (no effect) (Croissant & Millo, 2018) from January 2011 to December 2019 to evaluate which model is better.

5.7.2.2. Time Effects

Table 5.14: Testing Time Effects

F Test / Model	F	p-value
(1a)	20.308	< 2.2E-16
(1b)	20.305	< 2.2E-16

Notes: The null hypothesis of the F test is that the time effect is absent in the error. This test compares FE (time effect) and OLS (no effect) (Croissant & Millo, 2018) from January 2011 to December 2019 to evaluate which model is better.

Table 5.14 shows the F test to examine the existence of time effects or no effects in the errors for both models (1a) and (1b) from January 2011 to December 2019. All values of the p-value of the F test in Table 5.14 are less than the 5 per cent level in models (1a) and (1b). Therefore, the null hypothesis that the absence of time effects is strongly rejected in both models. This implies that time effects exist in the error and fixed effects (FE) are preferred to the OLS regression for both models.

5.7.2.3. Individual and Time Effects

Table 5.15 shows the F test to examine the existence of individual and time effects or no effects in the errors for both models (1a) and (1b) from January 2011 to December 2019. All values of the p-value of the F test in Table 5.15 are less than the 5 per cent level in models (1a) and (1b). Therefore, the null hypotheses that the absence of individual and time effects are strongly rejected in both models. This implies that both individual and time effects exist in the error and fixed effects (FE) are preferred to the OLS regression for both models.

Table 5.15: Testing Both Individual and Time Effects

F Test / Model	F	p-value
(1a)	11.906	< 2.2E-16
(1b)	11.919	< 2.2E-16

Notes: The null hypothesis of the F test is that the time effect is absent in the error. This test compares FE (individual and time effects) and OLS (no effect) (Croissant & Millo, 2018) from January 2011 to December 2019 to evaluate which model is better.

5.7.2.4. Individual Effects or Both Individual and Time Effects

Table 5.16: Individual Effects vs Both Individual and Time Effects

F Test / Model	F	p-value
(1a)	20.366	< 2.2E-16
(1b)	20.47	< 2.2E-16

Notes: The null hypothesis of the F test is the absence of time effect allowing for the presence of individual effect in the error. This test compares FE (individual and time effects) and FE (individual effect) (Croissant & Millo, 2018) from January 2011 to December 2019 to evaluate which model is better.

Table 5.16 shows the F test to examine the existence of individual effects or both individual and time effects in the errors for both models (1a) and (1b) from January 2011 to December 2019. All values of the p-value of the F test in Table 5.16 are less than the 5 per cent level in models (1a) and (1b). Therefore, the null hypotheses that the absence of time effects allows for the presence of individual effects are strongly rejected in both models. This implies that for fixed effects (FE) estimation, both individual and time effects in the error are preferred to the only individual effects in the error for both models.

5.7.2.5. Time Effects or Both Individual and Time Effects

Table 5.17 shows the F test to examine the existence of time effects or both individual and time effects in the errors for both models (1a) and (1b) from January 2011 to December 2019. All values of the p-value of the F test in Table 5.17 are less than the 5 per cent level in models (1a) and (1b). Therefore, the null hypotheses that the absence of individual effects allows for the presence of time effects are strongly rejected in both models. This implies that for fixed effects (FE) estimation, both individual and time effects in the error are preferred to the only time effects in the error for both models.

Table 5.17: Time Effects vs Both Individual and Time Effects

F Test / Model	F	p-value
(1a)	2.5158	1.113E-14
(1b)	2.5402	5.367E-15

Notes: The null hypothesis of the F test is the absence of individual effect allowing for the presence of time effect in the error. This test compares FE (individual and time effects) and FE (time effect) (Croissant & Millo, 2018) from January 2011 to December 2019 to evaluate which model is better.

5.8. Summary of Findings

5.8.1. Model Selection

The Hausman test in Section 5.7.1 shows that fixed effects (FE) are preferable to random effects (RE). Furthermore, the F tests in Section 5.7.2 also show that both individual and time effects have existed. Therefore, the panel regressions with both individual and time effects exist in the error and the FE estimation is more appropriate than RE and OLS estimations. Fama (2014) claims that FM estimation is a simple tool to study the cross-sections of stock returns; however, its advantage carries over to panels instead of taking averaging stock returns and other variables (BE estimation). However, the FM estimation is designed to explain only a time effect (Petersen, 2009), and the standard coefficients can be biased under individual effects. Because both individual and time effects exist in the data; therefore, using the FE estimations with both individual and time effects may improve the statistical inferences. Fama (2014) also recommends that with the development of panel regressions, clustering techniques are now available and should be applied to reduce biases. Therefore, the FE estimation using double clustering may be preferred to the FM and BE estimations. However, the results show that the BE estimation has higher adjusted R^2 than the FM estimation in both Panels A and B. This is similar to the finding in Claessens et al. (1995). Although the panel regressions using FE estimations with both individual and time effects are richer specifications than simple cross-sectional or time-series regressions and double clustering robustness can correct the standard errors of the coefficients (Croissant & Millo, 2018; Fama, 2014; Petersen, 2009; Thompson, 2011), this thesis found that they have extremely low adjusted R^2 compared to BE and FM estimations. Furthermore, the RMSE (root mean square error) of the BE is much lower than the FM and FE estimations. Therefore, the simple BE method seems to have a higher power in explaining the data on the HSX. However, the coefficients of this method may be biased because both time and individual effects are not considered. Table 5.18 below shows the coefficients after robustness using Newey and West (1987) for BE, FM estimations, and double clustering for the FE method. Table 5.19 shows the summary of the findings on the relationship between explanatory variables and stock returns in the HSX. The interpretations of these variables are shown in the next section.

Table 5.18: BE vs FM vs FE (Both Individual and Time Effects)

Models / Coefficients	BE (Newey–West)	FM (Newey–West)	FE (Double Effects) (Newey–West & Double Clustering)
Panel A: Model (1a)			
CAPM Beta	0.2866	−0.0532	0.2731
Firm Size	0.0889	−0.0951	**−3.2666*** **
Firm Value	−0.1234	0.2970	0.3109
Momentum	**0.0675*** **	**0.0165*** **	**0.0160*** **
VaR	0.0010	0.0100	0.0114
Illiquidity	**0.1001*** **	0.0224	−0.0204
Adjusted R^2	0.7952	0.2530	0.0005
RMSE	0.3299	9.1140	9.7842
Panel B: Model (1b)			
DCC Beta	0.2262	0.5371	**1.8653*** **
Firm Size	0.0803	−0.0898	**−3.3113*** **
Firm Value	−0.1282	0.1793	0.3173
Momentum	**0.0669*** **	**0.0148*** **	**0.0145*** **
CVaR	0.0025	−0.0047	−0.0212
Illiquidity	**0.0955*** **	0.0721	−0.0348
Adjusted R^2	0.7942	0.2681	0.0012
RMSE	0.3308	9.0214	9.7806

Notes:

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 5.19: Explanatory Variables of Stock Returns in the HSX

Variables	Hypotheses	Models		
		BE	FM	FE (double effects)
CAPM Beta	+	✕	✕	✕
DCC Beta	+	✕	✕	✓

Variables	Hypotheses	Models		
		BE	**FM**	**FE (double effects)**
Firm Size	−	×	×	✓
Firm Value	+	×	×	×
Momentum	+	✓	✓	✓
VaR	+	×	×	×
CVaR	−	×	×	×
Illiquidity	+	✓	×	×

Notes:

+ *: the variable and stock return are positively correlated*

− *: the variable and stock return are negatively correlated*

× *: reject the hypothesis*

✓ *: accept the hypothesis*

5.8.2. Coefficient Interpretations

5.8.2.1. CAPM Beta and DCC Beta

Both BE and FE (double effects) estimations in Table 5.18 show that CAPM beta in model (1a) is positively correlated with monthly stock return on the HSX, while FM estimation indicates that the relation between CAPM beta and stock returns is negative. Although different estimations show different results, CAPM beta and stock returns in the HSX are weak and statistically insignificant in all estimations. This result rejects the positive correlation between CAPM beta and stock returns in the HSX. This result also challenges the CAPM theory developed by Sharpe (1964). The rejection of CAPM beta in the HSX is similar to the results of research by Fama and French (1992), Bali et al. (2017) in the US, Novak and Petr (2010) in the Stockholm market, Shah et al. (2021) in the Pakistan market.

While the static beta (CAPM beta) cannot explain stock returns, the dynamic beta (DCC beta) can do it (Bali et al., 2017; Engle, 2002). The dynamic beta is efficient and effective in explaining stock returns in the US, Brazil, and G7 (Bali et al., 2017; Godeiro, 2013; Li, 2011; Vendrame et al., 2018). All estimations in Table 5.18 show that DCC beta in model (1b) is positively correlated with monthly stock return on the HSX. In particular, the FE (double effects) estimation found that DCC beta is significant at a 1 per cent level. The results show that if stocks have a higher DCC beta by 1 per cent, their returns will be higher by approximately 1.87 per cent under the FE (double effects) estimation. This supports the positive correlation between stock returns and dynamic betas in the HSX. Therefore, only the dynamic beta (DCC beta) is positively correlated with stock returns in the HSX (hypothesis HA1).

5.8.2.2. Firm Size

In the literature, firm size and stock returns are negatively correlated (Alhashel, 2021; Fama & French, 1992; Hou & Dijk, 2019; Vo et al., 2019). The size effects may be explained by the higher information risk of small-size companies (Banz, 1981). Furthermore, small firms may be related to higher financial distress (Chan & Chen, 1991; Hwang et al., 2010; Vassalou & Xing, 2004). Moreover, small stocks can be illiquid stocks (Amihud, 2002). Therefore, investors require higher returns for small-size stocks. Table 5.18 shows that while the BE estimation shows that firm size and monthly stock returns in the HSX are positively correlated, both FM and FE (double effects) estimations show that this correlation is negative in both models (1a) and (1b). However, the firm size is only significant in the HSX under FE (double effects) estimation at a 1 per cent level in both models. The FE (double effects) estimation shows that if stocks have a higher size by 1 per cent, their returns will be lower by approximately 3.3 per cent in both models. Therefore, the FE (double effects) estimation supports the negative correlation between firm size and stock returns in the HSX (hypothesis HA2). Both BE and FM estimations reject this relationship.

5.8.2.3. Firm Value

In the literature, firm value and stock returns are positively correlated (Alhashel, 2021; Fama & French, 1992; Hanauer & Lauterbach, 2019; Tsuji, 2020). Fama and French (1992) explain that the stock market considers the prospects of stocks with a high value measured by the high logarithm of the book-to-market ratio as poorer than stocks with low value. Therefore, high-value stocks have higher financial distress than low-value stocks. In addition, Lakonishok et al. (1994) state that a high book-to-market ratio is a signal of a company with unattractive growth. Therefore, it will have low market capitalisation, high risk, and a high book-to-market ratio. Table 5.18 shows that while the BE estimation shows that firm value and monthly stock returns in the HSX are negatively correlated, both FM and FE (double effects) estimations show that this correlation is positive in both models (1a) and (1b). However, all estimations show that the firm value is statistically insignificant in the HSX in both models. Therefore, the positive correlation between firm value and stock returns in the HSX (hypothesis HA3) is rejected by all estimations.

5.8.2.4. Momentum

In the literature, momentum and stock returns are positively correlated (Blackburn & Cakici, 2019; Fama & French, 1992; 1996; Hanauer & Lauterbach, 2019). The momentum effects can be explained by the underreaction to new information (Chan et al., 1996). These authors explain that investors slowly discount new information; therefore, a stock with low (high) past returns will continue low (high) subsequent returns. All estimations in Table 5.18 show that momentum in models (1a) and (1b) is positively correlated with monthly stock return on the HSX. In particular, all estimations show that the momentum is significant at a 1 per cent level. The BE estimation shows that if stocks have a higher momentum by 1 per cent, their returns will be higher by approximately 0.07 per cent in both models (1a) and (1b). Likewise, the FM and FE (double effects) estimations show that if stocks have a higher momentum by 1 per cent, their returns will be higher by approximately 0.016 per cent in both models. Therefore, the positive correlation between momentum and stock returns in the HSX (hypothesis HA4) is supported by all estimations.

5.8.2.5. Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR)

Higher VaR means higher loss; therefore, investors require higher returns for higher VaR stocks. In the literature, VaR and stock returns are positively correlated (Aziz & Ansari, 2017; Bali & Cakici, 2004; Chen et al., 2014; Iqbal & Azher, 2014). Table 5.18 shows that VaR in models (1a) and (1b) is positively correlated with monthly stock return on the HSX in all estimations. However, all estimations show that the VaR is statistically insignificant in all estimations. Therefore, the positive correlation between Value-at-Risk (VaR) and monthly stock return in the HSX (hypothesis HA5) is rejected.

Both VaR and CVaR are similar because they measure tail risks; therefore, CVaR and stock return are expected to be positively correlated. However, CVaR is negatively correlated with stock returns (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019). The findings that low-CVaR stocks have higher returns are counterintuitive because they violate the basic principle: high risk, high return. The low-CVaR effects can be explained by behavioural finance (Baker et al., 2011). First, many investors join the market but they lack the skills and knowledge to analyse securities. Therefore, a preference for lotteries and biases may exist, and the decisions of investors are irrational. Second, short selling is not allowed; therefore, those irrational demands cannot be offset by arbitrage. Table 5.18 also shows that while CVaR and monthly stock returns on the HSX are negatively correlated under FM and FE (double effects) estimations, this correlation is positive under the BE estimation. However, all estimations show that the CVaR is statistically insignificant in all estimations. Therefore, the negative correlation between conditional Value-at-Risk (CVaR) and monthly stock return in the HSX (hypothesis HA6) is rejected.

5.8.2.6. Illiquidity

In the literature, illiquidity and stock returns are positively correlated (Amihud, 2002; Chen et al., 2019; Chen & Sherif, 2016; Marcelo & Quirós, 2006). Illiquid stocks have higher transaction costs than liquid stocks (Amihud, 2002; Lesmond et al, 1999; Pástor & Stambaugh, 2003). Therefore, investors require higher returns for illiquid stocks. Table 5.18 shows that while the BE and FM estimations show that illiquidity and monthly stock returns in the HSX are positively correlated, the FE (double effects) estimation shows that this correlation is positive in both models (1a) and (1b). However, only the BE estimation shows that the illiquidity effect on stock returns is statistically significant at a 1 per cent level in the HSX in both models. The BE estimation shows that if stocks have higher illiquidity by 1 per cent, their monthly returns will be higher by approximately 0.1 per cent in both models (1a) and (1b). Therefore, the BE estimation supports the positive correlation between illiquidity and stock returns in the HSX (hypothesis HA7). Both FM and FE (both effects) estimations reject this relationship.

5.9. Conclusion

This chapter conducts different estimations including Fama–MacBeth regression (FM), between estimator (BE), fixed effects (FE), and random effects (RE) with different effects in the error. The study found that the standard errors of all estimations are biased (inflated or deflated). They should be enhanced by robustness using Newey and West (1987) or clustering (individual effects, time effects, or both effects) (Fama, 2014; Millo, 2017; 2019; Petersen, 2009; Thompson, 2011). Moreover, different estimations show different results. The BE estimation shows that only momentum and illiquidity are positive and significant in explaining stock returns on the HSX. In contrast, the FM estimation shows that only momentum is positive and significant. The FE estimation indicates that stock returns are positively and significantly correlated with momentum and DCC beta, but negatively correlated with firm size in this market. All three estimations reject the effects of CAPM beta, firm value, VaR, and CVaR on stock returns on the HSX. Chapter 6 tests different risk factors and select the appropriate risk model for the HSX using the GRS test.

Chapter 6: Testing Multifactor Models in the HSX

6.1. Introduction

The previous chapter studies the relationship between firm characteristics and stock returns. In this chapter, stocks are grouped into portfolios to reduce errors in variables that reduce bias and improve the efficiency and effectiveness of regressions (Ang et al., 2020; Fama & French, 1993; 2015; Jagannathan & Wang, 2002). This chapter studies nine common risk factors: the market portfolio (MKT) (Black et al., 1972; Sharpe, 1964), the size factor (SMB), and the value factor (HML) (Fama & French, 1993; Rashid et al., 2018; Xie & Qu, 2016), the momentum factor (UMD) (Carhart, 1997; Fama & French, 2012; Hanauer & Lauterbach, 2019), the Value-at-Risk factor (HVaRL) (Aziz & Ansari, 2017; Bali & Cakici, 2004; Chen et al., 2014), the illiquidity factor (HILLIQL) (Amihud, 2002; Bali & Cakici, 2004; Marcelo & Quirós, 2006), the profitability factor (RMW), and the investment factor (CMA) (Fama & French, 2015; Hou et al., 2015). Ling and Cao (2020), Tokpavi and Vaucher (2012), and Vo et al. (2019) found that stock returns are negatively correlated with conditional Value-at-Risk (CVaR) in China, the US, and Vietnam markets, respectively. Furthermore, the analysis in Chapter 5 also found that stock returns and CVaR are negative in the HSX in many estimations, except for the BE estimation. Based on this finding, this chapter creates and tests the CVaR factor (LCVaRH) as a new risk factor.

The risk factors are created by using multiple sort variables (Fama & French, 1993; 2012; 2015). This approach is effective for a large database; however, it is not efficient for a small sample. Skočir and Lončarski (2018) found that reducing breakpoints will increase the number of stocks in each portfolio and increase the power of factors. This thesis follows Banz (1981), Bali and Cakici (2004), and Amihud et al. (2015) using a single sort variable and the median breakpoint to build these common risk factors. This is simpler than using more sort variables, and it is appropriate with a small sample size for the HSX. Different factors models are tested to select the best one to be a benchmark for evaluating the performance of asset returns in the next chapter. The hypotheses between portfolio returns and their risk factors (HB1 to HB9) in Chapter 2 are tested. The construction of risk factors and portfolios are represented in Chapter 3. The descriptive statistics of these risk factors and portfolios are presented in Chapter 4.

6.2. The Combination of Risk Factors for the HSX

Table 6.1: Estimation Results for Multifactor Models

	MKT	MKT	MKT	MKT
	(1)	**(2)**	**(3)**	**(4)**
Alpha	0.373	0.271	0.589	0.387
	t = 0.787	t = 0.576	t = 1.213	t = 0.901
SMB	−0.651	−0.673	−0.743	−0.292
	t = −4.098***	**t = −4.219*****	**t = −4.733*****	**t = −2.127****
HML	0.556	0.412	0.341	0.279
	t = 3.953***	**t = 2.408****	t = 1.650	t = 1.552
UMD		−0.236		−0.116
		t = −2.380**		t = −1.468
LCVaRH				0.137
				t = 0.760
HVaRL				−0.132
				t = −0.685
HILLIQL				−0.669
				t = −6.937***
RMW			−0.148	0.009
			t = −0.760	t = 0.051
CMA			0.278	0.159
			t = 1.906*	t = 1.207
N	108	108	108	108
Adjusted R^2	0.184	0.212	0.206	0.422
F Statistic	**13.071*****	**10.586*****	**7.922*****	**10.778*****

Notes: the standard errors are robust using the method developed by Newey and West (1987). Data is monthly returns of risk factors from January 2011 to December 2019.

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 6.1 shows regressions of the monthly returns of the market portfolio (MKT) on monthly returns of other factors from January 2011 to December 2019. Fama and French (1993) state that if there are multiple common risk factors, they are all in the market portfolio (MKT). In other words, the return of the MKT is a combination of the risk factors. In detail, when running a regression of the MKT factor with other risk factors, risk factors having significant slopes will contribute to explaining stock returns. For example, Fama and French (1993) show that the slopes of SMB and HML factors are both significant when running a regression with the MKT factor. Therefore, a three-factor model (3FM) with MKT, SMB, and HML can explain stock returns where the SMB and HML explain the differences in average returns across assets; however, the MKT factor is needed to explain why stock returns are higher than the risk-free rate. Table 6.1 shows four regressions of the MKT on other risk factors. Estimations (1), (2), and (3) show the regression of the MKT on the SMB and HML (3FM, Fama & French, 1993), the MKT on the SMB, HML, and UMD (4FM, Carhart, 1997), the MKT on the SMB, HML, RMW, and CMA (5FM, Fama & French, 2015), respectively. Estimation (4) shows the regression of the MKT on the remaining factors which are considered risk factors.

The significant slopes on SMB and HML produced by MKT in estimation (1) are clear evidence that these factors capture common variations in stock returns. Hence, the 3FM (Fama & French, 1993) can be considered a risk model for the HSX. Similarly, because the slopes on SMB, HML, and UMD produced by MKT are significant in estimation (2), the 4FM (Carhart, 1997) also captures the variation of stock returns in this market. In estimation (3), only the slopes of SMB and CMA are significant, while the HML and RMW in the 5FM (Fama & French, 2015) are ineffective in the HSX. Therefore, only three factors in five factors explain stock returns in this market: MKT, SMB, and CMA. Similarly, estimation (4) shows that only the MKT, SMB, and HILLIQL contribute to explaining the stock returns for the HSX, other factors are explained by these factors.

The results from Table 6.1 show that different factor models can represent risk models for the HSX: the three-factor model (3FM) developed by Fama and French (Fama & French, 1993) with MKT, SMB, and HML factors; or the three-factor model with MKT, SMB, and CMA or the three-factor model with MKT, SMB, and HILLIQL factors, and four-factor model (4FM) developed by Carhart (1997). Table 6.2 shows the VIFs of risk factors from these multifactor models calculated from January 2011 to December 2019. The low VIF coefficients show that there is no multicollinearity in these multifactor models.

Table 6.2: VIFs of Multifactor Models

	MKT	**SMB**	**HML**	**UMD**	**CMA**	**HILLIQL**
3FM	1.249	2.487	2.315			
3FM	1.19	1.974			1.837	
3FM	1.376	2.052				2.562
4FM	1.305	2.556	2.671	1.687		

Notes: The VIFs are computed for risk factors from January 2011 to December 2019 for different multifactor models. If VIF is greater than 10, high multicollinearity is detected. Otherwise, the multicollinearity is rejected.

If a factor model explains expected returns, the intercept is indifferent from zero in a regression of excess returns of portfolios on factor returns (Black et al., 1972; Fama & French, 1993; 2015; Merton, 1973). The regression details of monthly excess returns of different portfolios on the returns of these factors and the univariate test (t-test) of intercepts are shown in Section 6.3. The multivariate test (Gibbons et al., 1989) (GRS test) for the best model in the HSX is shown in Section 6.4.

6.3. Multifactor Model Estimations

Tables 6.3, 6.4, 6.5, 6.6, 6.7, 6.8, and 6.9 show the estimation results for different factor models for Size–Value portfolios, Size–Momentum portfolios, Size–VaR portfolios, Size–CVaR portfolios, Size–Illiquidity portfolios, Size–CAPM beta portfolios, and Size–DCC beta portfolios, respectively. Panels A, B, and C show different there-factor models (MKT, SMB, and HML or MKT, SMB, and CMA, or MKT, SMB, and HILLIQ). Panel D shows the four-factor model (MKT, SMB, HML, and UMD).

6.3.1. Size–Value Portfolios

Table 6.3: Multifactor Models for Size–Value Portfolios

Portfolios / Factors	SH	SM	SL	BH	BM	BL
Panel A (3FM): MKT, SMB, HML						
Alpha	0.864	1.185	0.140	0.984	0.371	0.882
	t = 2.546**	**t = 3.053*****	t = 0.286	**t = 2.396****	t = 1.048	**t = 2.761*****
MKT	0.814	0.621	0.365	0.854	0.775	0.741
	t = 6.998***	**t = 10.416*****	**t = 2.305****	**t = 9.314*****	**t = 10.922*****	**t = 10.918*****
SMB	0.633	0.438	0.237	−0.286	−0.193	−0.315
	t = 3.749***	**t = 4.073*****	t = 1.329	t = −1.383	t = −1.533	**t = −2.600****
HML	0.215	0.202	0.320	1.035	0.539	−0.101
	t = 1.384	**t = 1.927***	**t = 2.486****	**t = 5.619*****	**t = 4.547*****	t = −0.941
Adjusted R^2	0.600	0.535	0.260	0.627	0.614	0.721
Panel B (3FM): MKT, SMB, CMA						
Alpha	0.828	1.190	0.112	1.045	0.464	0.839
	t = 2.332**	**t = 3.137*****	t = 0.235	**t = 1.860***	t = 1.111	**t = 2.652*****
MKT	0.865	0.652	0.431	1.002	0.827	0.742
	t = 8.416***	**t = 10.438*****	**t = 2.712*****	**t = 9.899*****	**t = 12.759*****	**t = 13.153*****
SMB	0.784	0.534	0.433	0.162	−0.035	−0.313
	t = 5.856***	**t = 4.406*****	**t = 2.718*****	t = 0.923	t = −0.294	**t = −3.665*****
CMA	0.011	0.094	0.070	0.560	0.426	−0.135
	t = 0.093	t = 0.706	t = 0.649	**t = 3.696*****	**t = 2.505****	**t = −1.701***
Adjusted R^2	0.590	0.524	0.230	0.508	0.581	0.723
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	0.800	1.138	0.088	0.789	0.260	0.881

Portfolios / Factors	SH	SM	SL	BH	BM	BL
	t = 2.222**	**t = 3.008*****	t = 0.172	t = 1.331	t = 0.610	**t = 3.141*****
MKT	0.687	0.597	0.509	1.108	0.829	0.566
	t = 6.392***	**t = 9.870*****	**t = 3.515*****	**t = 8.059*****	**t = 9.353*****	**t = 11.077*****
SMB	1.129	0.723	0.350	0.476	0.351	−0.105
	t = 8.759***	**t = 6.449*****	**t = 2.133****	**t = 2.443****	**t = 4.094*****	t = −1.324
HILLIQL	−0.565	−0.229	0.204	−0.0003	−0.246	−0.473
	t = −4.145***	**t = −2.062****	t = 1.402	t = −0.001	**t = −3.338*****	**t = −5.545*****
Adjusted R^2	0.659	0.538	0.241	0.465	0.554	0.789
Panel D (4FM): MKT, SMB, HML, UMD						
Alpha	0.837	1.116	0.192	0.937	0.365	0.866
	t = 2.462**	**t = 3.029*****	t = 0.410	**t = 1.850***	t = 1.009	**t = 2.808*****
MKT	0.801	0.586	0.392	0.830	0.772	0.733
	t = 6.700***	**t = 10.636*****	**t = 2.629*****	**t = 7.246*****	**t = 10.970*****	**t = 11.300*****
SMB	0.617	0.398	0.268	−0.313	−0.196	−0.324
	t = 3.686***	**t = 3.398*****	t = 1.555	t = −1.619	t = −1.572	**t = −2.758*****
HML	0.178	0.106	0.392	0.969	0.530	−0.123
	t = 1.162	t = 0.902	**t = 2.830*****	**t = 5.134*****	**t = 4.413*****	t = −1.163
UMD	−0.073	−0.189	0.144	−0.130	−0.017	−0.044
	t = −0.967	**t = −2.144****	**t = 1.777***	t = −1.274	t = −0.255	t = −0.627
Adjusted R^2	0.599	0.551	0.263	0.627	0.611	0.719

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 6.3 shows the regressions of excess monthly returns of six Size–Value portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A containing MKT, SMB, and HML produces high intercepts for the SH, SM, BH, and BL portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–Value portfolios on the HSX (Fama & French, 2015; Hou et al., 2015). In Panel B, when the HML factor is replaced by the CMA factor, this model reduces the intercepts of the SH and BL portfolios, while increasing the intercepts of the SM and BH portfolios. When the HML factor is replaced by the HILLIQL factor (Panel C) or adding UMD factor (Panel D), all these intercepts are reduced. In particular, the intercept of the BH portfolio in Panel C is insignificant. Therefore, replacing the HML factor with the CMA factor (Panel B) may improve the performance of SH and BL portfolios while replacing the HML factor with the HILLIQL (Panel C), or adding the UMD factor (Panel D) may improve the performance of SH, SM, BH, and BL portfolios.

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level. Therefore, returns of six Size–Value portfolios in the HSX move in the same direction as the market. When the value (measured by the book-to-market ratio) decreases, the MKT slopes decrease monotonically in both the small-size and big-size groups. In the small-size portfolios, the MKT slopes of the high-value (SH), the medium-value (SM), and the low-value (SL) portfolios are approximately 0.81, 0.62, and 0.37, respectively. Similarly, in the big-size portfolios, the MKT slopes of the high-value (BH), the medium-value (BM), and the low-value (BL) portfolios are approximately 0.85, 0.78, and 0.74, respectively. Hence, returns of the high-value portfolios vary larger than the returns of the low-value portfolios in both small-size and big-size groups when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios, SH (approximately 0.63), SM (approximately 0.44) and SL (approximately 0.24), but are negative for three big-size portfolios, BH (approximately −0.29), BM (approximately −0.19), and BL (approximately −0.32). In the small-size group, the SMB slopes of the high-value (SH) and medium-value (SM) portfolios are statistically significant at a 1 per cent level while in the big-size group, only the SMB slope of the low-value (BL) portfolio is significant at 5 per cent levels. When the book-to-market ratio decreases, the HML slopes increase non-monotonically in the small-size portfolios, but decrease monotonically in the big-size portfolios. In the small-size group, the HML slope of the low-value portfolio, SL (approximately 0.32) is higher than the slope of the medium-value portfolio, SM (approximately 0.20), but the HML slope of the medium-value portfolio is lower than the slope of the high-value portfolio, SH (approximately 0.22). In the big-size group, the HML slope of the low-value portfolio, BL (approximately −0.10) is lower than the slopes of the medium-value portfolio, BM (approximately 0.54), and the HML slope of the medium-value portfolio is lower than the slope of the high-value portfolio, BH (approximately 1.04). In the small-size group, the HML slopes of the medium-value (SM) and low-value (SL) portfolios are significant at 10 per cent and 5 per cent levels, respectively. In the big-size group, the HML slopes of the high-value (BH) and medium-value (BM) portfolios are significant at a 1 per cent level. In summary, the MKT factor is significant in explaining stock returns for all six Size–Value portfolios. While the SMB factor is significant for three Size–Value portfolios (SH, SM, and BL), the HML factor is significant for four Size–Value portfolios (SM, SL, BH, and BM). The average adjusted R^2 of 3FM in Panel A is approximately 56 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is slightly lower than the 3FM model in Panel A, approximately 3 per cent (53% compared to 56%). Most of the portfolio returns have positive CMA slopes. Only the BL portfolio return has a negative slope to this factor. The CMA slopes are between approximately −0.14 and 0.56. However, only the CMA slopes of the BH, BM, and BL portfolios are significant from 1 per cent to 10 per cent levels. Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for three Size–Value portfolios (BH, BM, and BL).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is slightly lower than the 3FM model in Panel A, approximately 2 per cent (54% compared to 56%). Most of the portfolio returns have negative HILLIQL slopes. Only the SL portfolio return has a positive slope to this factor. The HILLIQL slopes are between approximately −0.57 and 0.20. In the small-size group, the HILLIQL slopes of the high-value (SH) and medium-value (SM) portfolios are significant at 1 per cent and 5 per cent levels, respectively. In the big-size group, HILLIQL slopes of the medium-value (BM) and low-value (BL) portfolios are significant at a 1 per cent level. Therefore, controlling for the MKT and SMB, the HILLIQL factor is significant in explaining stock returns for four Size–Value portfolios (SH, SM, BM, and BL).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is similar to the 3FM in Panel A, at approximately 56 per cent. Most of the portfolio returns have negative UMD slopes. Only the SL portfolio return has a positive slope to this factor. The UMD slopes are between approximately −0.19 and 0.14. Only the UMD slopes of the SM and SL portfolios in the small-size group are significant at 5 per cent and 10 per cent levels, respectively. Therefore, controlling for the MKT, SMB, and HML, the UMD factor is significant in explaining stock returns for two Size–Value portfolios (SM and SL).

6.3.2. Size–Momentum Portfolios

Table 6.4: Multifactor Models for Size–Momentum Portfolios

Portfolios / Factors	SU	SN	SD	BU	BN	BD
Panel A (3FM): MKT, SMB, HML						
Alpha	1.621	1.024	0.135	0.905	0.548	−0.447
	t = 3.518* **	**t = 3.533*** **	t = 0.291	**t = 1.877***	t = 1.320	t = −1.026
MKT	0.541	0.512	0.910	0.597	0.818	1.023
	t = 4.957* **	**t = 9.030*** **	**t = 8.803*** **	**t = 7.496*** **	**t = 8.056*** **	**t = 8.102*** **
SMB	0.272	0.340	0.731	−0.418	−0.180	−0.047
	t = 1.864*	**t = 4.527*** **	**t = 3.483*** **	**t = −3.591*** **	t = −1.198	t = −0.273
HML	0.239	0.181	0.225	0.159	0.132	0.315
	t = 1.500	**t = 1.833***	t = 1.441	t = 1.339	t = 1.077	t = 1.486
Adjusted R^2	0.344	0.528	0.556	0.553	0.591	0.558
Panel B (3FM): MKT, SMB, CMA						
Alpha	1.599	0.967	0.163	0.872	0.580	−0.340
	t = 3.272* **	**t = 3.403*** **	t = 0.345	**t = 1.842***	t = 1.361	t = −0.818
MKT	0.589	0.567	0.936	0.637	0.827	1.031
	t = 6.079* **	**t = 8.801*** **	**t = 9.802*** **	**t = 8.886*** **	**t = 8.884*** **	**t = 9.021*** **

Portfolios / Factors	SU	SN	SD	BU	BN	BD
SMB	0.419	0.502	0.810	−0.298	−0.152	−0.020
	t = 4.518* **	**t = 5.573*** **	**t = 4.902*** **	**t = −3.720*** **	t = −1.170	t = −0.158
CMA	0.052	−0.052	0.155	−0.007	0.123	0.366
	t = 0.377	t = −0.544	t = 0.849	t = −0.056	t = 0.975	**t = 3.117*** **
Adjusted R^2	0.327	0.513	0.551	0.545	0.590	0.562
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	1.562	0.981	0.081	0.865	0.510	−0.523
	t = 3.113* **	**t = 3.029*** **	t = 0.167	t = 1.689*	t = 1.318	t = −1.184
MKT	0.493	0.486	0.874	0.554	0.743	0.972
	t = 4.268* **	**t = 6.754*** **	**t = 7.615*** **	**t = 7.181*** **	**t = 8.011*** **	**t = 9.383*** **
SMB	0.648	0.607	1.068	−0.148	0.119	0.425
	t = 5.866* **	**t = 4.753*** **	**t = 5.920*** **	t = −1.630	t = 0.979	**t = 3.067*** **
HILLIQL	−0.335	−0.222	−0.286	−0.256	−0.337	−0.402
	t = −2.417 **	**t = −1.747* **	t = −1.510	**t = −2.419** **	**t = −2.784*** **	**t = −2.169** **
Adjusted R^2	0.360	0.535	0.560	0.566	0.617	0.568
Panel D (4FM): MKT, SMB, HML, UMD						
Alpha	1.560	1.039	0.077	0.929	0.518	−0.580
	t = 3.425* **	**t = 3.198*** **	t = 0.175	t = 1.952*	t = 1.160	t = −1.325
MKT	0.510	0.520	0.881	0.609	0.802	0.956
	t = 4.723* **	**t = 9.708*** **	**t = 8.922*** **	**t = 7.241*** **	**t = 8.627*** **	**t = 10.556*** **
SMB	0.237	0.349	0.697	−0.404	−0.198	−0.124
	**t = 1.667* **	**t = 4.186*** **	**t = 3.584*** **	**t = −3.377*** **	t = −1.383	t = −0.675
HML	0.155	0.202	0.145	0.193	0.089	0.130
	t = 0.930	**t = 1.921* **	t = 0.955	t = 1.585	t = 0.708	t = 0.607
UMD	−0.165	0.042	−0.158	0.067	−0.084	−0.363
	t = −1.420	t = 0.737	t = −1.149	t = 0.633	t = −0.961	**t = −2.032** **
Adjusted R^2	0.352	0.525	0.559	0.552	0.590	0.593

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 6.4 shows the regressions of excess monthly returns of six Size–Momentum portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A containing MKT, SMB, and HML produces high intercepts for the SU, SN, and BU portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–Momentum portfolios on the HSX. When the HML factor is replaced by the CMA factor in Panel B, or by the HILLIQL in Panel C, the intercepts of these portfolios are reduced. However, they are still significant. The 4FM in Panel D shows that only the intercept of the SU portfolio is reduced, while the intercepts of SN and BU portfolios are increased. Therefore, replacing the HML factor with the CMA factor (Panel B), or with the HILLIQL (Panel C) may improve the performance of the model in Panel A. The 4FM improves the performance of the SU model; however, it reduces the performance of SN and BU compared to the 3FM in Panel A.

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level. Therefore, returns of six Size–Momentum portfolios in the HSX move in the same direction as the market. When the momentum decreases, the MKT slopes decrease monotonically in the small-size group, while these slopes increase monotonically in the big-size groups. In the small-size portfolios, the MKT slopes of the high-momentum or up-momentum (SU), the medium-momentum or neutral-momentum (SN), and the low-momentum or down-momentum (SD) portfolios are approximately 0.54, 0.51, and 0.91, respectively. In the big-size portfolios, the MKT slopes of the high-momentum (BU), the medium-momentum (BN), and the low-momentum (BD) portfolios are approximately 0.60, 0.82, and 1.02, respectively. Hence, the returns of the big-size portfolios vary larger than the returns of the small-size portfolios when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios: SU (approximately 0.27), SN (approximately 0.34) and SD (approximately 0.73), but are negative for three big-size portfolios: BU (approximately –0.42), BN (approximately –0.18), and BD (approximately –0.05). In the small-size group, the SMB slopes of all portfolios are statistically significant from 1 per cent to 10 per cent levels while in the big-size group, only the SMB slope of the high-momentum (BU) portfolio is significant at a 1 per cent level. Returns of all Size–Momentum portfolios have positive HML slopes. The HML slopes are between approximately 0.13 and 0.32. However, only the HML slope of the SN portfolio is significant at a 10 per cent level. In summary, the MKT factor is significant in explaining stock returns for all six Size–Momentum portfolios. While the SMB factor is significant for four Size–Momentum portfolios (SU, SN, SD, and BU), the HML factor is significant for only one Size–Momentum portfolio (SN). The average adjusted R^2 of the 3FM is approximately 52 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is similar to the 3FM model in Panel A, at approximately 52 per cent. Most of the portfolio returns have positive CMA slopes. Only the returns of SN and BL portfolios have negative slopes to this factor. The CMA slopes are between approximately -0.05 and 0.37. However, only the CMA slope of the BD portfolio is significant at a 1 per cent level. Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for only one Size–Momentum portfolio (BD).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is slightly higher than the 3FM model in Panel A, approximately 1 per cent (53% compared to 52%). Returns of Size–Momentum portfolios have negative HILLIQL slopes. The HILLIQL slopes are between approximately -0.40 and -0.22. In the small-size group, the HILLIQL slopes of the high-momentum (SU) and medium-momentum (SN) portfolios are significant at 5 per cent and 10 per cent levels, respectively. In the big-size group, all HILLIQL slopes are significant from 1 per cent to 5 per cent level. Therefore, controlling for the MKT and SMB factors, the HILLIQL factor is significant in explaining stock returns for five Size–Momentum portfolios (SU, SN, BU, BN, and BD).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is slightly higher than the 3FM model in Panel A, approximately 1 per cent (53% compared to 52%). Most of the portfolio returns have negative UMD slopes. When the momentum decreases, the UMD slopes increase non-monotonically in the small-size group, but decrease monotonically in the big-size group. In the small-size group, the UMD slope of the low-momentum portfolio, SD (approximately -0.16) is lower than the slope of the medium-momentum portfolio, SN (approximately 0.04), but the UMD slope of the medium-momentum portfolio is higher than the slope of the high-momentum portfolios, SU (approximately -0.17). In the big-size group, the UMD slope of the low-momentum portfolio, BD (approximately -0.36) is lower than the slope of the medium-momentum portfolio, BN (approximately -0.08), and the UMD slope of the medium-momentum portfolio is lower than the slope of the high-momentum portfolio, BU (approximately 0.07). However, only the UMD slope of the down-momentum in the big-size group (BD) is significant at a 5 per cent level. All UMD slopes in the small-size group are insignificant. Therefore, controlling for the MKT, SMB, and HML factors, the UMD factor is significant in explaining stock returns for only one Size–Momentum portfolio (BD).

6.3.3. Size–VaR Portfolios

Table 6.5 shows the regressions of excess monthly returns of six Size–VaR portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A (containing MKT, SMB, and HML) produces high intercepts for the SHVaR, SLVaR, BMVaR, and BLVaR portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–VaR portfolios on the HSX. In Panel B, when the HML factor is replaced by the CMA factor, this model reduces the intercepts of the SLVaR and BLVaR portfolios, while it increases the intercepts of the SHVaR and BMVaR portfolios. However, the intercept of these portfolios is still significant. In Panel C and D, when the HML factor is replaced by the HILLIQL factor or adding the UMD factor, all intercepts are reduced. In particular, the intercept of the BMVaR portfolio is insignificant in both Panels. Therefore, replacing the HML factor with the HILLIQL (Panel C), or adding the UMD factor (Panel D) may improve the performance of the model in Panel A. Panel B improves the performance of SMVaR and BLVaR portfolios, but not SHVaR and SLVaR.

Table 6.5: Multifactor Models for Size–VaR Portfolios

Factors \ Portfolios	SHVaR	SMVaR	SLVaR	BHVaR	BMVaR	BLVaR
Panel A (3FM): MKT, SMB, HML						
Alpha	1.704	0.284	0.636	−0.192	0.743	0.786
	t = 4.181***	t = 0.859	**t = 1.849***	t = −0.430	**t = 1.760***	**t = 2.028****
MKT	0.959	0.500	0.435	0.890	0.909	0.617
	t = 8.119***	**t = 9.548*****	**t = 7.157*****	**t = 8.882*****	**t = 8.077*****	**t = 8.089*****
SMB	0.722	0.260	0.380	−0.173	−0.085	−0.382
	t = 4.177***	**t = 2.969*****	**t = 4.665*****	t = −1.185	t = −0.571	**t = −3.273*****
HML	0.289	0.323	−0.023	0.678	0.165	−0.043
	t = 1.686*	**t = 3.044*****	t = −0.228	**t = 4.391*****	t = 1.252	t = −0.416
Adjusted R^2	0.611	0.606	0.372	0.597	0.566	0.590
Panel B (3FM): MKT, SMB, CMA						
Alpha	1.716	0.234	0.633	−0.160	0.855	0.752
	t = 3.879***	t = 0.645	**t = 2.053****	t = −0.311	**t = 2.189****	**t = 1.973***
MKT	1.002	0.574	0.432	0.990	0.890	0.624
	t = 9.408***	**t = 9.970*****	**t = 8.467*****	**t = 10.123*****	**t = 8.593*****	**t = 9.451*****
SMB	0.853	0.484	0.372	0.130	−0.140	−0.361
	t = 6.047***	**t = 5.016*****	**t = 3.348*****	t = 0.864	t = −1.148	**t = −4.475*****
CMA	0.144	0.025	−0.016	0.350	0.315	−0.093
	t = 0.857	t = 0.254	t = −0.153	**t = 2.080****	**t = 2.443****	t = −0.779
Adjusted R^2	0.601	0.555	0.372	0.532	0.581	0.592
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	1.630	0.219	0.630	−0.325	0.695	0.782
	t = 3.715***	t = 0.606	**t = 1.868***	t = −0.599	t = 1.557	**t = 2.127****
MKT	0.875	0.553	0.351	1.018	0.823	0.507
	t = 7.483***	**t = 8.924*****	**t = 6.287*****	**t = 8.813*****	**t = 8.456*****	**t = 7.177*****

Portfolios / Factors	SHVaR	SMVaR	SLVaR	BHVaR	BMVaR	BLVaR
SMB	1.226	0.548	0.511	0.399	0.274	−0.228
	t = 8.688* **	**t = 5.915*** **	**t = 5.783*** **	**t = 3.066*** **	**t = 1.958***	**t = −2.827*** **
HILLIQL	−0.487	−0.083	−0.246	−0.122	−0.397	−0.310
	t = −3.347* **	t = −1.047	**t = −2.458** **	t = −0.817	**t = −2.634*** **	**t = −3.042*** **
Adjusted R^2	0.635	0.558	0.409	0.514	0.595	0.620
Panel D (4FM): MKT, SMB, HML, UMD						
Alpha	1.634	0.283	0.608	−0.200	0.670	0.777
	t = 3.813* **	t = 0.876	**t = 1.774***	t = −0.456	t = 1.632	**t = 1.986** **
MKT	0.923	0.500	0.420	0.886	0.872	0.612
	t = 7.778* **	**t = 9.059*** **	**t = 6.845*** **	**t = 8.963*** **	**t = 9.369*** **	**t = 8.227*** **
SMB	0.681	0.260	0.364	−0.178	−0.127	−0.387
	t = 3.835* **	**t = 2.654*** **	**t = 4.151*** **	t = −1.228	t = −0.910	**t = −3.281*** **
HML	0.191	0.323	−0.062	0.667	0.065	−0.057
	t = 1.185	**t = 3.004*** **	t = −0.610	**t = 4.584*** **	t = 0.401	t = −0.527
UMD	−0.194	−0.001	−0.077	−0.023	−0.198	−0.027
	t = −1.646	t = −0.007	t = −1.038	t = −0.320	t = −1.184	t = −0.289
Adjusted R^2	0.618	0.602	0.373	0.593	0.577	0.586

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level. Therefore, returns of six Size–VaR portfolios in the HSX move in the same direction as the market. The MKT slopes decrease monotonically when the Value-at-Risk (VaR) decreases in the small-size group, but non-monotonically in the big-size group. In the small-size portfolios, the MKT slopes of the high-VaR (SHVaR), the medium-VaR (SMVaR), and the low-VaR (SLVaR) portfolios are approximately 0.96, 0.50, and 0.44, respectively. In contrast, in the big-size portfolios, the MKT slopes of the high-VaR (BHVaR), the medium-VaR (BMVaR), and the low-VaR (BLVaR) portfolios are approximately 0.89, 0.91, and 0.62, respectively. Hence, returns of the high-VaR portfolios vary larger than the returns of the low-

VaR portfolios in both small-size and big-size groups when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios, SHVaR (approximately 0.72), SMVaR (approximately 0.26) and SLVaR (approximately 0.38), but they are negative for three big-size portfolios, BHVaR (approximately -0.17), BMVaR (approximately -0.09), and BLVaR (approximately -0.38). The SMB slopes of all three small-size portfolios (SHVaR, SMVaR, and SLVaR) are statistically significant at a 1 per cent level; however, only the low-VaR portfolio in the big-size group (BLVaR) is statistically significant at the same 1 per cent level to the SMB. Most of the portfolio returns have positive HML slopes: SHVaR (approximately 0.29), SMVaR (approximately 0.32), BHVaR (approximately 0.68), and BMVaR (approximately 0.17). In contrast, returns of the SLVaR and BLVaR portfolios have negative HML slopes, approximately -0.02 and -0.04, respectively. In particular, the HML slope of the SHVaR portfolio is significant at a 10 per cent level. Both the HML slopes of the SMVaR and BHVaR portfolios are significant at a 1 per cent level. In summary, the MKT factor is significant in explaining stock returns for all six Size–VaR portfolios. While the SMB factor explains returns of the four Size–VaR portfolios (SHVaR, SMVaR, SLVaR, and BLVaR), the HML factor explains returns of the three Size–VaR portfolios (SHVaR, SMVaR, and BHVaR). The average adjusted R^2 of the 3FM in Panel A is approximately 56 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is slightly lower than the 3FM model in Panel A, approximately 2 per cent (54% compared to 56%). The returns of the SLVaR and BLVaR portfolios have negative CMA slopes, approximately -0.02 and -0.09, respectively. In contrast, returns of other portfolios have positive CMA slopes: SHVaR (approximately 0.14), SMVaR (approximately 0.03), BHVaR (approximately 0.35), and BMVaR (approximately 0.32). However, only the positive slopes of the BHVaR and BMVaR portfolios are significant at a 5 per cent level. Therefore, controlling for the MKT and

SMB factors, the CMA factor is significant in explaining stock returns of two Size–VaR portfolios (BHVaR and BMVaR).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is similar to the 3FM model in Panel A, at approximately 56 per cent. All returns of Size–VaR portfolios have negative HILLIQL slopes, between approximately -0.49 and -0.08. In the small-size group, HILLIQL slopes of the high-VaR (SHVaR, approximately -0.49) and low-VaR (SLVaR, approximately -0.25) portfolios are significant at 1 per cent and 5 per cent levels, respectively. In the big-size group, the HILLIQL slope of the medium-VaR portfolio (BMVaR, approximately -0.40) and the low-VaR portfolio (BLVaR, approximately -0.31) are significant at a 1 per cent level. Therefore, controlling for the MKT and SMB factors, the HILLIQL factor is significant in explaining stock returns of four Size–VaR portfolios (SHVaR, SLVaR, BMVaR, and BLVaR).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is similar to the 3FM in Panel A, at approximately 56 per cent. All six Size–VaR portfolios have negative UMD slopes, approximately from -0.2 to -0.001. However, all UMD slopes are insignificant for six Size–VaR portfolios. Therefore, controlling for the MKT and SMB factors, the UMD factor is redundant for 6 Size–VaR portfolios.

6.3.4. Size–CVaR Portfolios

Table 6.6 shows the regressions of excess monthly returns of six Size–CVaR portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A (containing MKT, SMB, and HML) produces high intercepts for the SHCVaR, SMCVaR, and BLCVaR portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–CVaR portfolios on the HSX. In Panel B, when the HML factor is replaced by the CMA factor, this model reduces the intercepts of the BLCVaR portfolios, while it increases the intercepts of the SHCVaR and SMCVaR portfolios. When the HML factor is replaced by the HILLIQL factor (Panel C) or adding UMD factor (Panel D), intercepts of SHCVaR and SMCVaR are reduced; however, the intercept of the BLCVaR portfolio is increased. Therefore, replacing the HML factor with the CMA factor (Panel B) may improve the performance of the BLCVaR portfolio, while replacing the HML factor with the HILLIQL factor (Panel C), or adding the UMD factor (Panel D) may improve the performance of the SHCVaR and SMCVaR portfolios.

Table 6.6: Multifactor Models for Size–CVaR Portfolios

Portfolios / Factors	SHCVaR	SMCVaR	SLCVaR	BHCVaR	BMCVaR	BLCVaR
Panel A (3FM): MKT, SMB, HML						
Alpha	1.391	0.674	0.555	−0.117	0.259	1.267
	t = 3.295* **	**t = 1.824***	t = 1.595	t = −0.324	t = 0.631	**t = 3.346*** **
MKT	0.904	0.632	0.361	0.854	0.814	0.663
	t = 7.483* **	**t = 10.796*** **	**t = 3.888*** **	**t = 8.649*** **	**t = 7.465*** **	**t = 9.016*** **
SMB	0.719	0.334	0.333	−0.231	−0.064	−0.347
	t = 3.679* **	**t = 4.145*** **	**t = 3.648*** **	**t = −1.722***	t = −0.375	**t = −2.582** **
HML	0.313	0.234	0.094	0.646	0.295	−0.140
	t = 1.772*	**t = 2.657*** **	t = 0.776	**t = 4.136*** **	**t = 2.401** **	t = −1.086
Adjusted R^2	0.589	0.615	0.300	0.616	0.540	0.625
Panel B (3FM): MKT, SMB, CMA						
Alpha	1.413	0.685	0.468	−0.042	0.418	1.172
	t = 3.301* **	**t = 1.778***	t = 1.333	t = −0.103	t = 1.113	**t = 3.130*** **
MKT	0.948	0.666	0.413	0.930	0.797	0.679
	t = 8.484* **	**t = 11.190*** **	**t = 6.845*** **	**t = 10.297*** **	**t = 7.669*** **	**t = 12.312*** **
SMB	0.850	0.438	0.486	0.002	−0.110	−0.301
	t = 5.591* **	**t = 4.217*** **	**t = 2.973*** **	t = 0.017	t = −0.818	**t = −3.329*** **
CMA	0.177	0.121	−0.151	0.432	0.471	−0.267
	t = 1.019	t = 1.264	t = −0.861	**t = 3.408*** **	**t = 3.661*** **	**t = −2.750*** **
Adjusted R^2	0.578	0.598	0.306	0.565	0.570	0.639
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	1.313	0.625	0.527	−0.240	0.188	1.275
	t = 3.002* **	t = 1.546	t = 1.572	t = −0.490	t = 0.409	**t = 3.587*** **

Portfolios / Factors		SHCVaR	SMCVaR	SLCVaR	BHCVaR	BMCVaR	BLCVaR
MKT		0.838	0.648	0.308	1.004	0.772	0.484
		t = 6.735* **	**t = 12.091*** **	**t = 3.560*** **	**t = 8.030*** **	**t = 7.568*** **	**t = 8.844*** **
SMB		1.220	0.583	0.545	0.259	0.368	−0.179
		t = 7.732* **	**t = 5.274*** **	**t = 4.346*** **	**t = 2.369** **	**t = 2.583** **	**t = −2.063** **
HILLIQL		−0.452	−0.130	−0.239	−0.026	−0.359	−0.453
		t = −2.777* **	t = −1.438	**t = −1.997** **	t = −0.181	**t = −2.495** **	**t = −4.743*** **
Adjusted R^2		0.605	0.599	0.324	0.530	0.550	0.681
Panel D (4FM): MKT, SMB, HML, UMD							
Alpha		1.352	0.634	0.540	−0.149	0.116	1.306
		t = 3.057* **	**t = 1.902***	t = 1.483	t = −0.415	t = 0.262	**t = 3.617*** **
MKT		0.885	0.612	0.353	0.838	0.742	0.682
		t = 6.770* **	**t = 10.961*** **	**t = 4.160*** **	**t = 8.490*** **	**t = 7.673*** **	**t = 8.825*** **
SMB		0.697	0.311	0.324	−0.249	−0.146	−0.325
		t = 3.578* **	**t = 3.277*** **	**t = 3.258*** **	**t = −1.801***	t = −1.044	**t = −2.365** **
HML		0.259	0.178	0.073	0.602	0.097	−0.087
		t = 1.612	**t = 1.723***	t = 0.518	**t = 4.226*** **	t = 0.709	t = −0.717
UMD		−0.106	−0.108	−0.041	−0.086	−0.390	0.105
		t = −1.119	t = −1.175	t = −0.459	t = −1.121	**t = −3.220*** **	t = 1.157
Adjusted R^2		0.588	0.620	0.295	0.615	0.603	0.627

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level. Therefore, six Size–CVaR portfolios in the HSX move in the same direction as the market. The MKT slopes increase monotonically when the conditional Value-at-Risk (CVaR) decreases in both small-size and big-size groups. In the small-size portfolios, the MKT slopes of the high-CVaR (SHCVaR), the medium-CVaR (SMCVaR), and the low-CVaR (SLCVaR) portfolios are approximately 0.90, 0.63, and 0.36, respectively. Similarly, in the big-size portfolios, the MKT slopes of the high-CVaR (BHCVaR), the medium-CVaR (BMCVaR), and the low-CVaR (BLCVaR) portfolios are approximately 0.85, 0.81, and 0.66, respectively.

Hence, returns of the high-CVaR portfolios vary larger than the medium-CVaR portfolio whose returns vary larger than the low-CVaR portfolio when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios, SHCVaR (approximately 0.72), SMCVaR and SLCVaR (approximately 0.33 for both portfolios), but are negative for three big-size portfolios, BHCVaR (approximately -0.23), BMCVaR (approximately -0.06), and BLCVaR (approximately -0.35). The SMB slopes of all three small-size portfolios (SHCVaR, SMCVaR, and SLCVaR) are statistically significant at a 1 per cent level; however, only the high-CVaR and low-CVaR portfolios in the big-size group (BHCVaR and BLCVaR) are statistically significant at a 10 per cent and 5 per cent levels to the SMB, respectively. Most returns of Size–CVaR portfolios have positive HML slopes, approximately between 0.09 and 0.65. Only the BLCVaR portfolio has a negative HML slope, approximately -0.14. The HML slopes of the SMCVaR and BHCVaR portfolios are significant at a 1 per cent level. The HML slopes of the SHCVaR and BMCVaR portfolios are significant at 10 per cent and 5 per cent levels, respectively. In summary, the MKT factor is significant in explaining stock returns for all six Size–CVaR portfolios. While the SMB factor is significant for five Size–CVaR portfolios (SHCVaR, SMCVaR, SLCVaR, BHCVaR, and BLCVaR), the HML factor explains returns for four Size–CVaR portfolios (SHCVaR, SMCVaR, BHCVaR, and BMCVaR). The average adjusted R^2 of the 3FM in Panel A is approximately 55 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is slightly lower than the 3FM model in Panel A, approximately 1 per cent (54% compared to 55%). Returns of SHCVaR, SMCVaR, BHCVaR, and BMCVaR portfolios have positive CMA slopes, approximately from 0.12 to 0.47. In contrast, returns of SLCVaR and BLCVaR portfolios have negative CMA slopes, approximately -0.15 and -0.27, respectively. However, only the slopes of the BHCVaR, BMCVaR, and BLCVaR are significant at a 1 per cent level.

Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for three Size–CVaR portfolios (BHCVaR, BMCVaR, and BLCVaR).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is similar to the 3FM model in Panel A, at approximately 55 per cent. All six Size–CVaR portfolios have negative HILLIQL slopes, approximately from -0.45 to -0.03. While the HILLIQL slope of the SHCVaR portfolio is significant at a 1 per cent level, the HILLIQL slopes of the SLCVaR, BMCVaR, and BLCVaR portfolios are significant at a 5 per cent level. Therefore, controlling for the MKT and SMB factors, the HILLIQL factor is significant in explaining stock returns for four Size–CVaR portfolios (SHCVaR, SLCVaR, BMCVaR, and BLCVaR).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is slightly higher than the 3FM in Panel A, approximately 1 per cent (56% compared to 55%). Most returns of six Size–CVaR portfolios have negative UMD slopes, except for the positive slope in the BLCVaR portfolio. The UMD slopes are approximately from -0.39 to 0.11. However, only the negative slope of the BMCVaR portfolio is significant at a 1 per cent level. Therefore, controlling for the MKT, SMB, and HML factors, the UMD factor is significant in explaining stock returns for only 1 portfolio (BMCVaR).

6.3.5. Size–Illiquidity Portfolios

Table 6.7 shows the regressions of excess monthly returns of six Size–Illiquidity portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A (containing MKT, SMB, and HML) produces high intercepts for the SHILLIQ, SMILLIQ, and BLILLIQ portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–Illiquidity portfolios on the HSX. In Panel B, when the HML factor is replaced by the CMA factor, this model reduces the intercepts of the SHILLIQ and BLILLIQ portfolios, while it increases the intercept of the SMILLIQ portfolio. When the HML factor is replaced by the HILLIQL factor (Panel C) or adding UMD factor (Panel D), all these three intercepts are reduced. Therefore, replacing the HML factor with the CMA factor (Panel B) may improve the performance of the SHILLIQ and BLILLIQ portfolios. In addition, replacing the HML factor with the HILLIQL factor (Panel C), or adding the UMD factor (Panel D) may improve the performance of all three portfolios.

Table 6.7: Multifactor Models for Size–Illiquidity Portfolios

Portfolios / Factors	SHILLIQ	SMILLIQ	SLILLIQ	BHILLIQ	BMILLIQ	BLILLIQ
Panel A (3FM): MKT, SMB, HML						
Alpha	1.155	0.909	−0.049	−0.019	0.464	0.853
	t = 3.440* **	**t = 2.358** **	t = −0.044	t = −0.043	t = 1.084	**t = 2.851*** **
MKT	0.402	0.773	1.127	0.051	0.593	0.781
	t = 4.174* **	**t = 8.290*** **	**t = 5.645*** **	t = 0.502	**t = 7.513*** **	**t = 10.665*** **
SMB	0.433	0.509	0.721	−0.093	0.044	−0.320
	t = 3.482* **	**t = 3.289*** **	**t = 2.322** **	t = −0.886	t = 0.410	**t = −2.372** **
HML	0.172	0.170	0.341	0.384	0.290	0.005
	t = 1.655	t = 1.318	t = 1.178	**t = 2.947*** **	**t = 2.124** **	t = 0.047
Adjusted R^2	0.449	0.618	0.331	0.080	0.451	0.742
Panel B (3FM): MKT, SMB, CMA						
Alpha	1.038	0.961	−0.165	0.038	0.528	0.824
	t = 3.050* **	**t = 2.500** **	t = −0.158	t = 0.090	t = 1.208	**t = 2.765*** **
MKT	0.480	0.780	1.232	0.091	0.615	0.794
	t = 4.683* **	**t = 10.684*** **	**t = 6.751*** **	t = 0.977	**t = 8.321*** **	**t = 13.648*** **
SMB	0.663	0.531	1.035	0.031	0.112	−0.282
	t = 5.230* **	**t = 4.759*** **	**t = 3.696*** **	t = 0.259	t = 1.220	**t = −3.069*** **
CMA	−0.186	0.183	−0.113	0.283	0.260	−0.061
	t = −1.306	**t = 2.191** **	t = −0.425	**t = 1.937***	**t = 1.922***	t = −0.779
Adjusted R^2	0.450	0.619	0.323	0.048	0.442	0.743
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	1.120	0.861	−0.145	−0.069	0.414	0.831
	t = 3.218* **	**t = 2.256** **	t = −0.138	t = −0.166	t = 0.938	**t = 3.151*** **
MKT	0.418	0.689	0.964	0.315	0.703	0.625
	t = 4.446* **	**t = 11.046*** **	**t = 4.805*** **	**t = 2.856*** **	**t = 7.191*** **	**t = 14.004*** **
SMB	0.608	0.871	1.437	−0.132	0.183	−0.019
	t = 3.689* **	**t = 5.823*** **	**t = 5.845*** **	t = −1.287	**t = 1.709***	t = −0.226

Portfolios / Factors	SHILLIQ	SMILLIQ	SLILLIQ	BHILLIQ	BMILLIQ	BLILLIQ
HILLIQL	−0.082	−0.396	−0.776	0.536	0.124	−0.497
	t = −0.626	**t = −2.745*****	**t = −3.403*****	**t = 4.093*****	t = 0.808	**t = −6.467*****
Adjusted R^2	0.438	0.654	0.364	0.133	0.424	0.819
Panel D (4FM): MKT, SMB, HML, UMD						
Alpha	1.136	0.864	−0.001	−0.107	0.451	0.839
	t = 3.474***	**t = 2.232****	t = −0.001	t = −0.244	t = 1.074	**t = 2.799*****
MKT	0.392	0.750	1.151	0.006	0.587	0.775
	t = 4.025***	**t = 9.417*****	**t = 5.533*****	t = 0.066	**t = 8.007*****	**t = 11.106*****
SMB	0.421	0.483	0.749	−0.145	0.036	−0.328
	t = 3.198***	**t = 3.136*****	**t = 2.295****	t = −1.290	t = 0.354	**t = −2.573****
HML	0.145	0.106	0.408	0.261	0.273	−0.013
	t = 1.629	t = 0.744	t = 1.435	**t = 1.981***	**t = 1.757***	t = −0.125
UMD	−0.052	−0.125	0.131	−0.242	−0.034	−0.036
	t = −0.623	**t = −1.699***	t = 0.705	**t = −2.497****	t = −0.429	t = −0.528
Adjusted R^2	0.446	0.622	0.326	0.112	0.446	0.740

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level, except for the insignificance in the high-illiquid portfolio in the big-size group (BHILLIQ). Therefore, six Size–Illiquidity portfolios in the HSX move in the same direction as the market. The MKT slopes increase monotonically when the illiquidity decreases in both small-size and big-size groups. In the small-size portfolios, the MKT slopes of the high-illiquid (SHILLIQ), the medium-illiquid (SMILLIQ), and the low-illiquid (SLILLIQ) portfolios are approximately 0.40, 0.77, and 1.13, respectively. Similarly, in the big-size portfolios, the MKT slopes of the high-illiquid (BHILLIQL), the medium-illiquid (BMILLIQL), and the low-illiquid (BLILLIQL) portfolios are approximately 0.05, 0.59, and 0.78, respectively. Hence, returns of lower-illiquid portfolios vary larger than higher-illiquid portfolios when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios, SHILLIQ (approximately 0.43), SMILLIQ (approximately 0.51), and SLILLIQ (approximately 0.72), but are negative for two over three big-size portfolios, BHILLIQ (approximately -0.09), BMILLIQ (approximately 0.04), and BLILLIQ (approximately -0.32). The SMB slopes of all three small-size portfolios (SHILLIQ, SMILLIQ, and SLILLIQ) are statistically significant from 1 per cent to 5 per cent levels; however, only the low-illiquid portfolio in the big-size group (BLILLIQ) is statistically significant at a 5 per cent level to the SMB. All returns of six Size–Illiquidity portfolios have positive HML slopes, approximately between 0.005 and 0.38. However, only the HML slopes of the BHILLIQ and BMILLIQ portfolios are significant at 1 per cent and 5 per cent levels, respectively. In summary, the MKT factor is significant in explaining stock returns for five Size–Illiquidity portfolios, except for the BHILLIQ portfolio. While the SMB factor is significant for four Size–Illiquidity portfolios (except for the BHILLIQ and BMILLIQ portfolios), the HML factor is significant for two Size–Illiquidity portfolios (BHILLIQ and BMILLIQ). The average adjusted R^2 of the 3FM in Panel A is approximately 45 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is slightly lower than the 3FM model in Panel A, approximately 1 per cent (44% compared to 45%). Returns of the SHILLIQ, SLILLIQ, and BLILLIQ portfolios have negative CMA slopes, approximately -0.19, -0.11, and -0.06, respectively. In contrast, returns of the SMILLIQ, BHILLIQ, and BMILLIQ portfolios have positive CMA slopes, approximately 0.18, 0.28, and 0.26, respectively. However, only the CMA slopes of the SMILLIQ, BHILLIQ, and BMILLIQ portfolios are statistically significant. Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for three Size–Illiquidity portfolios (SMILLIQ, BHILLIQ, and BMILLIQ).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is slightly higher than the 3FM model in Panel A, approximately 2 per cent (47% compared to 45%). Returns of SHILLIQ, SMILLIQ, SLILLIQ, and BLILLIQ portfolios have negative HILLIQL slopes, approximately from -0.78 to -0.08. In contrast, returns of the BHILLIQ and BMILLIQ portfolios have positive HILLIQL slopes, approximately 0.54 and 0.12, respectively. The slopes of SMILLIQ, SLILLIQ, BHILLIQ, and BLILLIQ portfolios are significant at a 1 per cent level. Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for four Size–Illiquidity portfolios (SMILLIQ, SLILLIQ, BHILLIQ, and BLILLIQ).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is similar to the 3FM in Panel A, at approximately 45 per cent. Most returns of six Size–Illiquidity portfolios have negative UMD slopes, except for the positive slope in the SLILLIQ portfolio. The UMD slopes are approximately from -0.24 to 0.13. However, only the UMD slopes of the SMILLIQ and BHILLIQ portfolios are significant at 10 per cent and 5 per cent levels, respectively. Therefore, controlling for the MKT, SMB, and HML factors, the UMD factor is significant in explaining stock returns for two Size–Illiquidity portfolios (SMILLIQ and BHILLIQ).

6.3.6. Size–CAPM Beta Portfolios

Table 6.8 shows the regressions of excess monthly returns of six Size–CAPM beta portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A (containing MKT, SMB, and HML) produces high intercepts for the SHCAPM, SMCAPM, and SLCAPM portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–CAPM beta portfolios on the HSX. In Panel B, when the HML factor is replaced by the CMA factor, this model reduces the intercepts of the SMCAPM and SLCAPM portfolios while it increases the intercept of the SHCAPM portfolio. In particular, the intercept of the SMCAPM portfolio is statistically insignificant. When the HML factor is replaced by the HILLIQL factor (Panel C) or adding UMD factor (Panel D), all these three intercepts are reduced. While the intercepts of SHCAPM and SMCAPM are statistically insignificant in Panel C, the intercept of SHCAPM is insignificant in Panel D. Therefore, replacing the HML factor with the CMA factor (Panel B) may improve the performance of the SMCAPM and SLCAPM portfolios. In addition, replacing the HML factor with the HILLIQL factor (Panel C), or adding the UMD factor (Panel D) may improve the performance of all three portfolios.

Table 6.8: Multifactor Models for Size–CAPM Beta Portfolios

Factors \ Portfolios	SHCAPM	SMCAPM	SLCAPM	BHCAPM	BMCAPM	BLCAPM
Panel A (3FM): MKT, SMB, HML						
Alpha	0.833	0.642	1.209	0.296	0.601	0.679
	t = 1.706*	**t = 1.880***	**t = 3.278*****	t = 1.065	t = 1.193	t = 1.429
MKT	1.071	0.588	0.390	1.088	0.906	0.366
	t = 9.734***	**t = 6.892*****	**t = 3.491*****	**t = 9.407*****	**t = 6.925*****	**t = 3.903*****
SMB	0.728	0.313	0.518	−0.108	−0.113	−0.314
	t = 3.833***	**t = 2.302****	**t = 3.213*****	t = −0.497	t = −0.715	**t = −2.725*****
HML	0.197	0.314	0.062	0.349	0.247	0.063
	t = 1.217	**t = 2.620****	t = 0.448	**t = 2.785*****	t = 1.454	t = 0.565
Adjusted R^2	0.588	0.535	0.354	0.667	0.542	0.292
Panel B (3FM): MKT, SMB, CMA						
Alpha	0.896	0.577	1.138	0.361	0.722	0.642
	t = 1.895*	t = 1.579	**t = 3.053*****	t = 1.203	t = 1.452	t = 1.344
MKT	1.078	0.668	0.430	1.120	0.897	0.392
	t = 10.181***	**t = 7.956*****	**t = 4.435*****	**t = 10.842*****	**t = 9.060*****	**t = 3.977*****
SMB	0.750	0.551	0.636	−0.012	−0.137	−0.237
	t = 3.931***	**t = 4.302*****	**t = 3.407*****	t = −0.068	t = −1.317	**t = −2.304****
CMA	0.219	−0.012	−0.130	0.286	0.368	−0.054
	t = 1.246	t = −0.104	t = −0.699	**t = 2.800*****	**t = 2.646*****	t = −0.340
Adjusted R^2	0.588	0.500	0.359	0.658	0.555	0.292
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	0.779	0.571	1.191	0.214	0.537	0.660
	t = 1.543	t = 1.457	**t = 3.287*****	t = 0.616	t = 1.021	t = 1.358

Portfolios / Factors	SHCAPM	SMCAPM	SLCAPM	BHCAPM	BMCAPM	BLCAPM
MKT	0.984	0.577	0.354	1.052	0.838	0.329
	t = 8.955* **	**t = 7.874*** **	**t = 3.470*** **	**t = 12.897*** **	**t = 6.026*** **	**t = 3.672*** **
SMB	1.128	0.711	0.659	0.380	0.312	−0.169
	t = 7.383* **	**t = 5.774*** **	**t = 3.270*** **	**t = 1.933* **	**t = 2.553** **	t = −1.446
HILLIQL	−0.426	−0.279	−0.160	−0.385	−0.406	−0.164
	t = −3.048* **	**t = −2.229** **	t = −1.051	**t = −2.530** **	**t = −2.697*** **	t = −1.190
Adjusted R^2	0.608	0.526	0.363	0.671	0.563	0.302
Panel D (4FM): MKT, SMB, HML, UMD						
Alpha	0.798	0.599	1.207	0.255	0.471	0.716
	t = 1.549	**t = 1.741* **	**t = 3.254*** **	t = 0.866	t = 1.052	t = 1.351
MKT	1.053	0.567	0.389	1.068	0.841	0.385
	t = 9.420* **	**t = 7.371*** **	**t = 3.567*** **	**t = 10.423*** **	**t = 7.803*** **	**t = 3.524*** **
SMB	0.707	0.289	0.517	−0.132	−0.188	−0.292
	t = 3.584* **	**t = 2.097** **	**t = 3.076*** **	t = −0.649	t = −1.263	**t = −2.481** **
HML	0.147	0.255	0.059	0.292	0.067	0.116
	t = 0.873	**t = 2.072** **	t = 0.445	**t = 1.849* **	t = 0.413	t = 1.016
UMD	−0.098	−0.117	−0.006	−0.112	−0.355	0.103
	t = −1.115	t = −1.219	t = −0.055	t = −0.989	**t = −2.829*** **	t = 1.130
Adjusted R^2	0.586	0.539	0.348	0.668	0.584	0.293

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level; therefore, six Size–CAPM beta portfolios in the HSX move in the same direction as the market. The MKT slopes decrease monotonically when the CAPM beta decreases in both small-size and big-size groups. In the small-size portfolios, the MKT slopes of the high-CAPM beta (SHCAPM), the medium-CAPM beta (SMCAPM), and the low-CAPM beta (SLCAPM) portfolios are approximately 1.07, 0.59, and 0.39, respectively. Similarly, in the big-size portfolios, the MKT slopes of the high-CAPM beta (BHCAPM), the medium-CAPM beta (BMCAPM), and the low-CAPM beta (BLCAPM) portfolios are approximately 1.09, 0.91, and

0.37, respectively. Hence, the returns of the high-CAPM portfolios vary larger than the medium-CAPM beta portfolio whose returns vary larger than the low-CAPM beta portfolio when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios, SHCAPM (approximately 0.73), SMCAPM (approximately 0.31), and SLCAPM (approximately 0.52), but are negative for the three big-size portfolios, BHCAPM and BMCAPM (approximately -0.11), and BLCAPM (approximately -0.31). The SMB slopes of all three small-size portfolios are statistically significant: SHCAPM and SLCAPM (significant at a 1% level), SMCAPM (significant at a 5% level); however, only the low-CAPM beta portfolio (BLCAPM) in the big-size group is statistically significant at a 1 per cent level to the SMB. All returns of six Size–CAPM beta portfolios have positive HML slopes, approximately between 0.06 and 0.35. However, only the slopes of the SMCAPM and BHCAPM portfolios are significant at 5 per cent and 1 per cent levels, respectively. In summary, the MKT factor is significant in explaining stock returns for all six Size–CAPM beta portfolios. While the SMB factor is significant for four Size–CAPM portfolios (SHCAPM, SMCAPM, SLCAPM, and BLCAPM), the HML factor is significant for two Size–CAPM portfolios (SMCAPM and BHCAPM). The average adjusted R^2 of the 3FM in Panel A is approximately 50 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is slightly lower than the 3FM model in Panel A, approximately 1 per cent (49% compared to 50%). Returns of the SMCAPM, SLCAPM, and BLCAPM have negative CMA slopes, approximately -0.01, -0.13, and -0.05, respectively. In contrast, returns of the SHCAPM, BHCAPM, and BMCAPM portfolios have positive CMA slopes, approximately 0.22, 0.29, and 0.37, respectively. However, only the positive slope of the BMCAPM portfolio is significant at a 5 per cent level. Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for two Size–CAPM beta portfolios (BHCAPM and BMCAPM).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is slightly higher than the 3FM model in Panel A, approximately 1 per cent (51% compared to 50%). All six returns of the Size–CAPM beta portfolios have negative HILLIQL slopes, approximately between -0.43 and -0.16. While HILLIQL slopes of SHCAPM and BMCAPM portfolios are significant at a 1 per cent level, those slopes of SMCAPM and BHCAPM portfolios are significant at a 5 per cent level. Therefore, controlling for the MKT and SMB factors, the HILLIQL factor is significant in explaining stock returns for four Size–CAPM beta portfolios (SHCAPM, SMCAPM, BHCAPM, and BMCAPM).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is similar to the 3FM in Panel A, at approximately 50 per cent. Most returns of six Size–CAPM beta portfolios have negative UMD slopes, except for the positive UMD slope in the BLCAPM portfolio. The UMD slopes are approximately from -0.36 to 0.10. However, only the UMD slope of the BMCAPM portfolio is significant at a 1 per cent level. Therefore, controlling for the MKT, SMB, and HML factors, the UMD factor is significant in explaining stock returns for only one portfolio (BMCAPM).

6.3.7. Size–DCC Beta Portfolios

Table 6.9 shows the regressions of excess monthly returns of six Size–DCC beta portfolios on different multifactor models from January 2011 to December 2019. The 3FM in Panel A (containing MKT, SMB, and HML) produces high intercepts for the SLDCC and BMDCC portfolios. This shows that the MKT, SMB, and HML factors do not explain all the risks for the Size–DCC beta portfolios on the HSX. In Panel B, when the HML factor is replaced by the CMA factor, this model increases the intercepts of these portfolios. Furthermore, the model in

Panel B cannot capture the risk of the SMDCC and BHDCC portfolios. The alphas of these two portfolios are positive and significant. When the HML factor is replaced by the HILLIQL factor (Panel C), it reduces the intercepts of SLDCC and BMDCC portfolios in Panel A. In contrast, adding the UMD factor (Panel D) increases these intercepts. While the intercepts of SHCAPM and SMCAPM are statistically insignificant in Panel C, the intercept of SHCAPM is insignificant in Panel D. Therefore, replacing the HML factor with the CMA factor (Panel B) or adding the UMD factor (Panel D) may deteriorate the performance of the model in Panel A. In contrast, replacing the HML factor with the HILLIQL factor (Panel C) may improve the performance of this model.

Table 6.9: Multifactor Models for Size–DCC Beta Portfolios

Factors \ Portfolios	SHDCC	SMDCC	SLDCC	BHDCC	BMDCC	BLDCC
Panel A (3FM): MKT, SMB, HML						
Alpha	0.739	0.625	1.093	0.283	1.322	−0.071
	t = 1.308	t = 1.448	**t = 3.156*** **	t = 0.986	**t = 2.776*** **	t = −0.212
MKT	1.351	0.741	0.216	1.106	0.485	0.150
	t = 10.355* **	**t = 9.216*** **	**t = 2.772*** **	**t = 12.391*** **	**t = 5.502*** **	**t = 1.859***
SMB	0.636	0.420	0.362	−0.082	−0.363	−0.014
	t = 2.741* **	**t = 3.912*** **	**t = 2.879*** **	t = −0.492	**t = −2.993*** **	t = −0.132
HML	0.395	0.197	0.205	0.167	−0.092	0.235
	t = 2.218 **	**t = 1.744***	**t = 1.895***	t = 1.440	t = −0.739	**t = 2.194** **
Adjusted R^2	0.609	0.636	0.367	0.725	0.513	0.100
Panel B (3FM): MKT, SMB, CMA						
Alpha	0.821	0.696	0.952	0.406	1.254	−0.055
	t = 1.492	**t = 1.703***	**t = 2.557** **	**t = 1.672***	**t = 2.594** **	t = −0.155
MKT	1.383	0.745	0.309	1.083	0.498	0.182
	t = 11.190* **	**t = 10.253*** **	**t = 3.771*** **	**t = 14.329*** **	**t = 5.710*** **	**t = 2.149** **
SMB	0.734	0.433	0.638	−0.149	−0.326	0.085
	t = 4.109* **	**t = 5.211*** **	**t = 5.249*** **	t = −1.223	**t = −3.818*** **	t = 0.837
CMA	0.344	0.236	−0.224	0.339	−0.187	0.133
	t = 2.007 **	**t = 2.748*** **	**t = −1.801***	**t = 3.440*** **	t = −1.546	t = 1.372
Adjusted R^2	0.604	0.640	0.369	0.740	0.522	0.074

Portfolios / Factors	**SHDCC**	**SMDCC**	**SLDCC**	**BHDCC**	**BMDCC**	**BLDCC**
Panel C (3FM): MKT, SMB, HILLIQL						
Alpha	0.637	0.582	1.045	0.237	1.318	−0.095
	t = 1.235	t = 1.309	**t = 2.909*** **	t = 0.784	**t = 3.150*** **	t = −0.253
MKT	1.237	0.741	0.192	1.035	0.303	0.362
	t = 9.829* **	**t = 9.150*** **	**t = 2.157** **	**t = 13.636*** **	**t = 3.601*** **	**t = 3.926*** **
SMB	1.324	0.657	0.654	0.252	−0.129	−0.132
	t = 6.737* **	**t = 5.476*** **	**t = 4.413*** **	**t = 1.752* **	t = −1.260	t = −1.175
HILLIQL	−0.664	−0.153	−0.235	−0.353	−0.502	0.485
	t = −3.260* **	t = −1.232	**t = −2.080** **	**t = −2.473** **	**t = −5.195*** **	**t = 3.896*** **
Adjusted R^2	0.636	0.631	0.373	0.743	0.605	0.214
Panel D (4FM): MKT, SMB, HML, UMD						
Alpha	0.663	0.565	1.111	0.195	1.351	−0.099
	t = 1.226	t = 1.359	**t = 3.254*** **	t = 0.619	**t = 2.597** **	t = −0.290
MKT	1.314	0.711	0.225	1.062	0.500	0.136
	t = 10.702* **	**t = 10.396*** **	**t = 2.997*** **	**t = 13.833*** **	**t = 4.558*** **	t = 1.412
SMB	0.592	0.385	0.372	−0.133	−0.346	−0.030
	t = 2.748* **	**t = 3.458*** **	**t = 2.846*** **	t = −0.913	**t = −2.915*** **	t = −0.291
HML	0.290	0.113	0.230	0.045	−0.051	0.196
	t = 1.554	t = 0.998	**t = 2.169** **	t = 0.344	t = −0.446	**t = 1.738* **
UMD	−0.206	−0.164	0.049	−0.241	0.079	−0.076
	t = −1.628	**t = −2.795*** **	t = 0.569	**t = −2.438** **	t = 0.763	t = −0.852
Adjusted R^2	0.612	0.648	0.363	0.742	0.513	0.098

Notes: The regressions are conducted from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

The 3FM in Panel A shows that all slopes of the MKT are positive and significant at a 1 per cent level; therefore, six Size–DCC beta portfolios in the HSX move in the same direction as the market. The MKT slopes decrease monotonically when the DCC beta decreases in both small-size and big-size groups. In the small-size portfolios, the MKT slopes of the high-DCC beta (SHDCC), the medium-DCC beta (SMDCC), and the low-DCC beta (SLDCC) portfolios are approximately 1.35, 0.74, and 0.22, respectively. Similarly, in the big-size portfolios, the MKT slopes of the high-DCC beta (BHDCC), the medium-DCC beta (BMDCC), and the low-DCC beta (BLDCC) portfolios are approximately 1.11, 0.49, and 0.15, respectively. Hence, the returns of the high-DCC portfolios vary larger than the medium-DCC beta portfolio whose returns vary larger than the low-DCC beta portfolio when the market fluctuates. The small-size portfolios have higher SMB slopes than the big-size portfolios. The SMB slopes are positive for the three small-size portfolios, SHDCC (approximately 0.64), SMDCC (approximately 0.42), and SLDCC (approximately 0.36), but are negative for the three big-size portfolios, BHDCC (approximately -0.08), BMDCC (approximately -0.36), and BLDCC (approximately -0.01). The SMB slopes of all three small-size portfolios (SHDCC, SMDCC, and SLDCC) and the medium-DCC beta portfolio (BMDCC) in the big-size group are statistically significant at a 1 per cent level. Most returns of six Size – DCC beta portfolios have positive HML slopes, except for the negative HML slope in the BMDCC portfolio. The slopes are approximately from -0.09 to 0.24. While the slopes of SHDCC and BLDCC portfolios are significant at a 5 per cent level, the slopes of SMDCC and SLDCC portfolios are significant at a 10 per cent level. In summary, the MKT factor is significant in explaining stock returns for all six Size–CAPM beta portfolios. The SMB and HML factors are significant for four Size–DCC portfolios. The average adjusted R^2 of the 3FM in Panel A is approximately 49 per cent.

In Panel B, the average adjusted R^2 of the alternative 3FM (MKT, SMB, and CMA) is similar to the 3FM model in Panel A, at approximately 49 per cent. Returns of SHDCC, SMDCC, BHDCC, and BLDCC have positive CMA slopes, approximately from 0.13 to 0.34. In contrast, returns of SLDCC and BMDCC portfolios have negative CMA slopes, approximately -0.22 and -0.19, respectively. The CMA slopes of the small-size group are statistically significant: SHDCC (significant at a 5% level), SMDCC (significant at a 1% level), and SLDCC (significant at a 10% level). However, only the CMA slope of the BHDCC portfolio in the big-size group is significant at a 1 per cent level. Therefore, controlling for the MKT and SMB factors, the CMA factor is significant in explaining stock returns for four Size–DCC beta portfolios (SHDCC, SMDCC, SLDCC, and BHDCC).

In Panel C, the average adjusted R^2 of another 3FM (MKT, SMB, and HILLIQL) is slightly higher than the 3FM model in Panel A, approximately 4 per cent (53% compared to 49%). Most returns of six Size–DCC beta portfolios have negative HILLIQL slopes, except for the positive slope in the BLDCC portfolio. The HILLIQL slopes are approximately between -0.67 and 0.49. While HML slopes of SHDCC, BMDCC, and BLDCC portfolios are significant at a 1 per cent level, those slopes of SLDCC and BDCC portfolios are significant at a 5 per cent level. Therefore, controlling for the MKT and SMB factors, the HILLIQL factor is significant in explaining stock returns for five Size–DCC beta portfolios (except for the SMDCC).

In Panel D, the average adjusted R^2 of the 4FM (MKT, SMB, HML, and UMD) is slightly higher than the 3FM in Panel A, approximately 1 per cent (50% compared to 49%). Returns of SHDCC, SMDCC, BHDCC, and BLDCC portfolios have negative UMD slopes, approximately from -0.24 to -0.08. In contrast, returns of SLDCC and BMDCC portfolios have positive UMD slopes, approximately 0.05 and 0.08, respectively. However, only the UMD slopes of the SMDCC and BHDCC portfolios are significant at 1 per cent and 5 per cent levels, respectively. Therefore, controlling for the MKT, SMB, and HML factors, the UMD factor is significant in explaining stock returns for two Size–DCC beta portfolios (SMDCC and BHDCC).

6.4. Testing Factor Models

Multifactor models are important in finance because they can be used to test the efficiency of the stock market or to evaluate the performance of portfolios (Fama, 2014). However, Hanauer and Lauterbach (2019) state that popular multifactor models are tested in the US or developed markets, they may be not appropriate for developing markets because of the differences in market structures. In addition, the significance of published factors is disappear or decays over time because arbitrageurs can learn about mispricing of these factors for their trading (Jacobs & Müller, 2020; Mclean & Pontiff, 2016). Furthermore, Harvey and Liu (2019) show that more than 300 factors affect stock returns. Therefore, multifactor models should be tested before use or researchers can create new ones. This chapter tests nine risk factors: the market portfolio (MKT) in the CAPM model developed by Sharpe (1964), size factor (SMB), value factor (HML), profitability factor (RMW), investment factor (CMA) developed by Fama and French (2015), momentum factor (UMD) developed by Carhart (1997), illiquidity factor (HILLIQL) and Value-at-Risk factor (HVaRL) developed by Bali and Cakici (2004), and a new conditional Value-at-Risk factor (LCVaRH) constructed based on the negative correlation between conditional Value-at-Risk and stock returns (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019). The constructions of these factors are shown in Chapter 3.

Table 6.10: The GRS Test

Portfolios	**Factors**	**F-Statistics**	**p-Values**
Size–Value	MKT, SMB, HML	2.261	0.044
	MKT, SMB, CMA	2.078	0.062
	MKT, SMB, HILLIQL	2.716	0.017
	MKT, SMB, HML, UMD	2.095	0.061
Size–Momentum	MKT, SMB, HML	4.096	0.001
	MKT, SMB, CMA	3.583	0.003
	MKT, SMB, HILLIQL	3.973	0.001
	MKT, SMB, HML, UMD	4.167	0.001
Size–VaR	MKT, SMB, HML	3.158	0.007
	MKT, SMB, CMA	3.140	0.007
	MKT, SMB, HILLIQL	3.691	0.002
	MKT, SMB, HML, UMD	2.973	0.010
Size–CVaR	MKT, SMB, HML	2.915	0.012
	MKT, SMB, CMA	2.597	0.022
	MKT, SMB, HILLIQL	3.442	0.004

Portfolios	Factors	F-Statistics	p-Values
	MKT, SMB, HML, UMD	2.998	0.010
Size–Iliquidity	MKT, SMB, HML	2.744	0.017
	MKT, SMB, CMA	2.435	0.031
	MKT, SMB, HILLIQL	3.930	0.001
	MKT, SMB, HML, UMD	2.634	0.021
Size–CAPM Beta	MKT, SMB, HML	2.468	0.029
	MKT, SMB, CMA	2.097	0.060
	MKT, SMB, HILLIQL	2.417	0.032
	MKT, SMB, HML, UMD	2.458	0.029
Size–DCC Beta	MKT, SMB, HML	3.054	0.009
	MKT, SMB, CMA	2.703	0.018
	MKT, SMB, HILLIQL	4.343	0.001
	MKT, SMB, HML, UMD	3.161	0.007

Notes: The GRS test is computed for different multifactor models in different portfolios from January 2011 to December 2019. The null hypothesis of the GRS test is that all intercepts are equal to zero simultaneously. If the null hypothesis is rejected, the market is inefficient. Otherwise, the market is efficient.

Table 6.10 shows the GRS test for different multifactor models in different portfolios from January 2011 to December 2019. The null hypothesis of the GRS test is that all intercepts of all factor models are equal to zero simultaneously (Gibbons et al., 1989; Kim, 1995). For the Size–Value portfolios, the three-factor model (containing MKT, SMB, and CMA) and the four-factor model (containing MKT, SMB, HML, and UMD) pass the GRS test at a 5 per cent level with high p-values (approximately 6.2% and 6.1%, respectively). They have better performance than the three-factor model using MKT, SMB, and HML with a low p-value (approximately 4.4%) in risk explanation. For Size–CAPM beta portfolios, only the three-factor model (containing MKT, SMB, and CMA) passes the GRS test at a 5 per cent level with a high p-value (approximately 6%), the GRS test of other models is below this hurdle rate. For the Size–Momentum and Size–VaR portfolios, the GRS test rejects all factor models in the previous section because all p-values are lower than 5 per cent. Therefore, all intercepts of multifactor models are different from zero and all models cannot explain all risks. Similarly, for other portfolios (Size–CVaR, Size– Illiquidity, Size–DCC beta), all multifactor models fail the GRS test at a 5 per cent level; however, the three-factor model containing MKT, SMB, and CMA seems better than other multifactor models because of higher p-values and it passes the GRS test at a 1 per cent level.

6.5. Summary of Findings

Although the 3FM (MKT, SMB, and HML factors) developed by Fama and French (1993) and 4FM (MKT, SMB, HML, and UMD factors) developed by Carhart (1997) are popularly used to evaluate the performance of portfolios in both developed and developing market (Fama, 2014; Hanauer & Lauterbach, 2019; Hu et al., 2019), these models are inefficient to explain risks for the HSX because of the low p-values from the GRS test (Table 6.10). Also, not all the factors in the 5FM developed by Fama and French (2015) are considered risk factors in this market because the HML and RMW factors are insignificant (Table 6.1). However, the remaining three factors (MKT, SMB, and CMA) can explain the returns of portfolios. The combination of these three factors (MKT, SMB, and CMA) shows the best performance to explain the returns for the HSX because the p-values from the GRS test are higher and more significant compared to other combinations (Table 6.10).

6.6. Conclusions

This chapter studies nine risk factors are studied including MKT, SMB, HML, UMD, HVaRL, LCVaRH, HILLIQL, RMW, and CMA. All mimicking-portfolio factors are constructed using a single sort variable and median breakpoint rather than using double sort variables to increase the number of stocks in each portfolio (high and low) and increase the power of these factors in a small sample size in emerging countries. The GRS tests show that the 3FM model containing the MKT, SMB, and CMA factors has a better performance than other multifactor models. This model passes the GRS test from 1 per cent to 5 per cent levels, except for the Size–Momentum and Size–VaR portfolios. Therefore, the combination of the MKT, SMB, and

CMA may be the best risk model for the HSX. This model is used as a benchmark to evaluate the performance of different strategies in the next chapter.

Chapter 7: Stock Selection for Trading Strategies

7.1. Introduction

In Chapter 2, the literature shows some evidence that stock returns are negatively correlated with firm size and conditional Value-at-Risk (CVaR), while positively correlated with firm value (book-to-market ratio), momentum, Value-at-Risk (VaR), illiquidity, CAPM beta, and DCC beta. In Chapter 5, different estimations show different results after robustness. While the between-estimator technique shows that only momentum and illiquidity are positively correlated with stock returns on the HSX, the Fama–MacBeth regression indicates that only momentum is positively correlated with stock returns on this market. In contrast, the fixed effects with both individual and time effects show that stock returns on the HSX are positively correlated with DCC beta and momentum, but negatively correlated with size. The GRS test in Chapter 6 found that the three-factor model (3FM) containing the MKT, SMB, and CMA has a higher performance than other models. Therefore, the alpha (intercept) of this model can be used to evaluate the performance of stock selection in this chapter.

This chapter is based on this information to build appropriate strategies to find positive returns. Different stock selections from A to O (see Chapter 3 for details) are tested using both nonparametric and parametric methods. The nonparametric method uses t-statistics to test if the returns of strategies are significantly positive over time. In contrast, the parametric method uses the alphas of the 3FM model containing the MKT, SMB, and CMA developed in Chapter 6 to test the returns of long and arbitrage strategies that are undervalued, overvalued, or predicted by the market (represented by the 3FM model). First, trading strategies are formed based on the full sample data (single sort variable). Second, stocks are separated into small and big-size and big-size groups. Then, in each group, stocks are sorted again based on firm value, momentum, VaR, CVaR, illiquidity, CAPM beta, and DCC beta (double sort variable) to enhance the test. The details of these strategies are represented in Chapter 3.

7.2. Single Sort and Strategies

This section uses a single sort and breaks the sample stocks into three portfolios using the 30th and 70th percentiles based on each firm characteristic. The performance of long and arbitrage strategies is tested by nonparametric and parametric methods on portfolio returns. The nonparametric method uses a t-test. The parametric method uses alphas which are the intercepts of the regressions of returns of these long and arbitrage strategies on the returns of the MKT, SMB, and CMA factors. The details of the strategies are represented below.

7.2.1. Size Portfolios and Strategies

Table 7.1: Size Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Smaller Size – Bigger Size)		
	S	**M**	**B**	**S–M**	**S–B**	**M–B**
Monthly Returns (%)	2.269	1.371	1.398	0.898	0.870	−0.028
	t = 3.407* **	**t = 2.553** **	**t = 2.696*** **	**t = 2.122** **	t = 1.405	t = −0.061
Monthly Alphas (%)	1.809	1.071	1.476	0.737	0.333	−0.404
	t = 5.678* **	**t = 3.128*** **	**t = 4.693*** **	**t = 2.606** **	t = 1.424	**t = −2.216** **

Notes: Monthly returns and alphas are computed for three size portfolios and the difference returns between smaller-size and bigger-size portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 7.1 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size from January 2011 to December 2019. Stocks are sorted into three size portfolios (S, M, and B) using the 30th and 70th percentiles breakpoints of the firm size. Based on the hypothesis that stock returns are negatively correlated with firm size, returns of smaller-size stocks should be higher than returns of bigger-size stocks. Therefore, the arbitrage strategies that buy smaller-size stocks and sell bigger-size stocks should have positive returns. The returns of long strategies are excess monthly returns of the three size portfolios. The returns of arbitrage strategies are excess monthly returns of the smaller-size portfolios minus excess monthly returns of the bigger-size portfolios.

There are three long strategies: buying stocks in the small-size portfolio (S), the medium-size portfolio (M), and the big-size portfolio (B). Table 7.1 shows that the excess monthly returns of all three long strategies are positive and statistically significant at a 1 per cent level for both S and B portfolios, and at a 5 per cent level for the M portfolio. In addition, these returns outperform the market because the monthly alphas are positive and significant at a 1 per cent level. However, the excess monthly return of the S portfolio (approximately 2.27%) is higher than those of the M portfolio (approximately 1.37%), and the B portfolio (approximately 1.40%). Therefore, for long strategies, buying stocks in the S portfolio earns a higher excess monthly return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the small-size portfolio and selling stocks in the medium-size portfolio (S–M), buying stocks in the small-size portfolio and selling stocks in the big-size portfolio (S–B), buying stocks in the medium-size portfolio and selling stocks in the big-size portfolio (M–B). Table 7.1 shows that the monthly return of the S–B strategy is insignificant (indifferent from zero) and predicted by the market because the alpha is insignificant. While the monthly return of the M–B portfolio underperforms the market because the alpha is negative and significant at a 5 per cent level, this return is insignificant (indifferent from zero). Only the monthly return of the S–M strategy is positive (approximately 0.9%) and significant at a 5 per cent level. Furthermore, this strategy outperforms the market because the monthly alpha is positive and significant at a 5 per cent level. Therefore, for arbitrage strategies, the S–M arbitrage strategy earns a higher return than the others and this return outperforms the market. However, the monthly return of the arbitrage strategy (S–M) (approximately 0.9%) is lower than that of the long strategy that buys stocks in the S portfolio (approximately 2.27%). In addition, this long strategy outperforms the market. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on firm size, investors should buy stocks in the S portfolio to maximise the excess monthly return.

7.2.2. Value Portfolios and Strategies

Table 7.2: Value Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Higher Value – Lower Value)		
	L	**M**	**H**	**H–L**	**H–M**	**M–L**
Monthly Returns (%)	1.311	1.549	2.109	0.799	0.560	0.239
	t = 2.458**	**t = 2.481****	**t = 3.517*****	t = 1.130	t = 1.136	t = 0.451
Monthly Alphas (%)	1.365	1.463	1.910	0.545	0.447	0.098
	t = 3.569***	**t = 2.881*****	**t = 3.668*****	t = 1.228	t = 0.933	t = 0.242

Notes: Returns and alphas are computed for three value portfolios and the difference returns between higher-value and lower-value portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 7.2 shows the average monthly returns and alphas of long and arbitrage strategies based on firm value from January 2011 to December 2019. Stocks are sorted into three value portfolios (L, M, and H) using the 30th and 70th percentiles breakpoints of the firm value. Based on the hypothesis that stock returns are positively correlated with firm value, returns of higher-value stocks should be higher than returns of lower-value stocks. Therefore, arbitrage strategies that buy higher-value stocks and sell lower-value stocks should have positive returns. The returns of long strategies are excess monthly returns of the three value portfolios. The returns of arbitrage strategies are excess monthly returns of the higher-value portfolios minus excess monthly returns of the lower-value portfolios.

There are three long strategies: buying stocks in the low-value portfolio (L), the medium-value portfolio (M), and the high-value portfolio (H). Table 7.2 shows that the excess monthly returns of all three long strategies are positive and statistically significant at a 5 per cent level for L and M portfolios, and at a 1 per cent level for the H portfolio. In addition, these returns outperform the market because the monthly alphas are positive and significant at a 1 per cent level. However, the excess monthly return of the H portfolio (approximately 2.11%) is higher than those of the M portfolio (approximately 1.55%), and the L portfolio (approximately 1.31%). Therefore, for long strategies, buying stocks in the H portfolio earns a higher excess monthly return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the high-value portfolio and selling stocks in the low-value portfolio (H–L), buying stocks in the high-value portfolio and selling stocks in the medium-value portfolio (H–M), buying stocks in the medium-value portfolio and selling stocks in the low-value portfolio (M–L). Table 7.2 shows that monthly returns of all arbitrage strategies are insignificant (indifferent from zero), and they are predicted by the market (all alphas are insignificant). Therefore, none of the arbitrage strategies earn a positive return. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on firm value (book-to-market ratio), investors should buy stocks in the H portfolio. This long strategy not only earns the highest excess monthly return (approximately 2.11%) but this return also outperforms the market (the alpha is approximately 1.9% monthly).

7.2.3. Momentum Portfolios and Strategies

Table 7.3 shows the average monthly returns and alphas of long and arbitrage strategies based on momentum from January 2011 to December 2019. Stocks are sorted into three momentum portfolios (D, N, and U) using the 30th and 70th percentiles breakpoints of the momentum. Based on the hypothesis that stock returns are positively correlated with momentum, returns of higher-momentum stocks should be higher than returns of lower-momentum stocks. Therefore, arbitrage strategies that buy higher-momentum stocks and sell lower-momentum stocks should have positive returns. The returns of long strategies are excess monthly returns of the three momentum portfolios. The returns of arbitrage strategies are excess monthly returns of the higher-momentum portfolios minus excess monthly returns of the lower-momentum portfolios.

Table 7.3: Momentum Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Higher Momentum – Lower Momentum)		
	D	**N**	**U**	**U–D**	**U–N**	**N–D**
Monthly Returns (%)	0.560	1.302	1.469	0.909	0.167	0.742
	t = 0.878	**t = 2.276****	**t = 2.807*****	t = 1.330	t = 0.393	**t = 2.360****
Monthly Alphas (%)	0.390	1.283	1.563	1.174	0.280	0.893
	t = 0.944	**t = 3.208*****	**t = 3.327*****	**t = 1.887***	t = 0.528	**t = 2.215****

Notes: Returns and alphas are computed for three momentum portfolios and the difference returns between higher-momentum and lower-momentum portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

There are three long strategies: buying stocks in the down-momentum (low-momentum) portfolio (D), the neutral-momentum (medium-momentum) portfolio (N), and the up-momentum (high-momentum) portfolio (U). Table 7.3 shows that the excess monthly return of the D portfolio is insignificant (indifferent from zero), and this is predicted by the market (the alpha is insignificant). Both returns of the N and U portfolios are positive and significant at 5 per cent and 1 per cent levels, respectively. In addition, these returns outperform the market because the alphas are positive and significant at a 1 per cent level. However, the excess return of the U portfolio (approximately 1.47%) is higher than that of the N portfolio (approximately

1.3%). Therefore, for long strategies, buying stocks in the U portfolio earns a higher return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the up-momentum portfolio and selling stocks in the down-momentum portfolio (U–D), buying stocks in the up-momentum portfolio and selling stocks in the neutral-momentum portfolio (U–N), buying stocks in the neutral-momentum portfolio and selling stocks in the down-momentum portfolio (N–D). Table 7.3 shows that the monthly return of the U-N strategy is insignificant (indifferent from zero), and this return is predicted by the market (the alpha is insignificant). The return of the U–D strategy outperforms the market (the alpha is positive and significant at a 10% level) but this return is insignificant (indifferent from zero). Only the monthly return of the N–D strategy is positive (approximately 0.74%) and significant at a 5 per cent level. Furthermore, this strategy outperforms the market because the alpha is positive and significant at a 5 per cent level. Therefore, for arbitrage strategies, only the N–D strategy earns a higher return than the others and this return outperforms the market. However, the monthly return of the arbitrage strategy (N-D) (approximately 0.74%) is lower than that of the long strategy that buys stocks in the U portfolio (approximately 1.47%). In addition, the return of this long strategy outperforms the market. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on momentum, investors should buy stocks in the U portfolio to maximise the return.

7.2.4. VaR Portfolios and Strategies

Table 7.4 shows the average monthly returns and alphas of long and arbitrage strategies based on Value-at-Risk (VaR) from January 2011 to December 2019. Stocks are sorted into three VaR portfolios (LVaR, MVaR, and HVaR) using the 30th and 70th percentiles breakpoints of the VaR. Based on the hypothesis that stock returns are positively correlated with VaR, returns of higher-VaR stocks should be higher than returns of lower-VaR stocks. Therefore, arbitrage strategies that buy higher-VaR stocks and sell lower-VaR stocks should have positive returns. The returns of long strategies are excess monthly returns of the three VaR portfolios. The returns of arbitrage strategies are excess monthly returns of the higher-VaR portfolios minus excess monthly returns of the lower-VaR portfolios.

Table 7.4: VaR Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Higher VaR – Lower VaR)		
	LVaR	**MVaR**	**HVaR**	**HVaR–LVaR**	**HVaR–MVaR**	**MVaR–LVaR**
Monthly Returns (%)	1.248	1.519	1.096	−0.152	−0.423	0.271
	t = 2.220**	**t = 2.222****	t = 1.571	t = −0.187	t = −0.760	t = 0.435
Monthly Alphas (%)	1.381	1.497	0.823	−0.557	−0.674	0.116
	t = 3.611***	**t = 3.858*****	**t = 1.729***	t = −0.969	t = −1.230	t = 0.256

Notes: Returns and alphas are computed for three VaR portfolios and the difference returns between higher-VaR and lower-VaR portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

There are three long strategies: buying stocks in the low-VaR portfolio (LVaR), the medium-VaR portfolio (MVaR), and the high-VaR portfolio (HVaR). Table 7.4 shows that although the excess monthly return of the (HVaR) portfolio outperforms the market (the alpha is positive and significant at a 10% level), this return is insignificant (indifferent from zero). Both excess returns of the LVaR and MVaR portfolios are positive and significant at a 5 per cent level. In addition, these returns outperform the market because the alphas are positive and significant at a 1 per cent level. However, the excess monthly return of the MVaR portfolio (approximately 1.52%) is higher than that of the LVaR portfolio (approximately 1.25%). Therefore, for long strategies, buying stocks in the MVaR portfolio earns a higher excess monthly return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the high-VaR portfolio and selling stocks in the low-VaR portfolio (HVaR–LVaR), buying stocks in the high-VaR portfolio and selling stocks in the medium-VaR portfolio (HVaR–MVaR), buying stocks in the medium-VaR portfolio and selling stocks in the low-VaR portfolio (MVaR–LVaR). Table 7.4 shows that the monthly returns of all these strategies are insignificant (indifferent from zero) and they are predicted by the market (all alphas are insignificant). Therefore, none of the arbitrage strategies earn a positive return. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on Value-at-Risk, investors should buy stocks in the MVaR portfolio to maximise the return. This long strategy not only earns the highest monthly return (approximately 1.52%), but this return also outperforms the market (the monthly alpha is approximately 1.9%).

7.2.5. CVaR Portfolios and Strategies

Table 7.5: CVaR Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Lower CVaR – Higher CVaR)		
	LCVaR	**MCVaR**	**HCVaR**	**LCVaR–MCVaR**	**LCVaR–HCVaR**	**MCVaR – HCVaR**
Monthly Returns (%)	1.718	1.090	0.988	0.627	0.729	0.102
	t = 3.111* **	t = 1.642	**t = 1.716***	t = 0.975	t = 1.026	t = 0.257
Monthly Alphas (%)	1.794	1.071	0.824	0.723	0.970	0.247
	t = 4.774* **	**t = 2.886*** **	**t = 2.109** **	**t = 1.756***	**t = 2.015** **	t = 0.594

Notes: Returns and alphas are computed for three CVaR portfolios and the difference returns between lower-CVaR and higher-CVaR portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 7.5 shows the average monthly returns and alphas of long and arbitrage strategies based on conditional Value-at-Risk (CVaR). Stocks are sorted into three CVaR portfolios (LCVaR, MCVaR, and HCVaR) using the 30th and 70th percentiles breakpoints of the CVaR. Based on the hypothesis that stock returns are negatively correlated with CVaR, returns of lower-VaR stocks should be higher than returns of higher-CVaR stocks. Therefore, arbitrage strategies that buy lower-CVaR stocks and sell higher-CVaR stocks should have positive returns. The returns of long strategies are excess monthly returns of the three CVaR portfolios. The returns of arbitrage strategies are excess monthly returns of the lower-CVaR portfolios minus excess monthly returns of the higher-VaR portfolios.

There are three long strategies: buying stocks in the low-CVaR portfolio (LCVaR), the medium-CVaR portfolio (MCVaR), and the high-CVaR portfolio (HCVaR). Table 7.5 shows that the excess monthly return of the MCVaR portfolio outperforms the market because the alpha is positive and significant at a 1 per cent level. However, this return is insignificant (indifferent from zero). The excess returns of strategies that buy stocks in the LCVaR and HCVaR portfolios are positive and significant at 1 per cent and 10 per cent levels, respectively. In addition, these returns outperform the market because the alphas are positive and significant at 1 per cent and 5 per cent levels for the LCVaR and HCVaR portfolios, respectively. However, the excess monthly return of the LCVaR portfolio (approximately 1.72%) is higher than that of the HCVaR portfolio (approximately 0.99%). Therefore, for long strategies, buying stocks in the LCVaR portfolio earns a higher return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the low-CVaR portfolio and selling stocks in the medium-CVaR portfolio (LCVaR–MCVaR), buying stocks in the low-CVaR portfolio and selling stocks in the high-CVaR portfolio (LCVaR–HCVaR), buying stocks in the medium-CVaR portfolio and selling stocks in the high-CVaR portfolio (MCVaR–HCVaR). Table 7.5 shows that the monthly return of the MCVaR–HCVaR strategy is insignificant (indifferent from zero) and this return is predicted by the market because the alpha is insignificant. While the returns of the LCVaR–MCVaR and LCVaR–HCVaR portfolios outperform the market because the monthly alphas are positive and significant at 10 per cent and 5 per cent levels, respectively, these returns are insignificant (indifferent from zero). Therefore, none of the arbitrage strategies earn a positive return. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on conditional Value-at-Risk, investors should buy stocks in the LCVaR portfolio to maximise the return. This long strategy not only earns the highest monthly return (approximately 1.72%), but this return also outperforms the market (the monthly alpha is approximately 1.79%).

7.2.6. Illiquidity Portfolios and Strategies

Table 7.6: Illiquidity Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Higher Illiquidity – Lower Illiquidity)		
	LIlliq	**MIlliq**	**HIlliq**	**HIlliq–LIlliq**	**HIlliq–MIlliq**	**MIlliq–LIlliq**
Monthly Returns (%)	1.392	1.531	1.480	0.088	−0.051	0.138
	t = 2.640* **	**t = 2.564** **	**t = 3.056*** **	t = 0.161	t = −0.120	t = 0.291
Monthly Alphas (%)	1.458	1.384	1.296	−0.162	−0.088	−0.073
	t = 4.701* **	**t = 3.278*** **	**t = 3.791*** **	t = −0.537	t = −0.242	t = −0.309

Notes: Returns and alphas are computed for three illiquidity portfolios and the difference returns between higher-illiquidity and lower-illiquidity portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 7.6 shows the average monthly returns and alphas of long and arbitrage strategies based on illiquidity from January 2011 to December 2019. Stocks are sorted into three illiquidity portfolios (LIlliq, MIlliq, and HIlliq) using the 30th and 70th percentiles breakpoints of the illiquidity. Based on the hypothesis that stock returns are positively correlated with illiquidity, returns of higher-illiquidity stocks should be higher than returns of lower-illiquidity stocks. Therefore, arbitrage strategies that buy higher-illiquidity stocks and sell lower-illiquidity stocks should have positive returns. The returns of long strategies are excess monthly returns of the three illiquidity portfolios. The returns of arbitrage strategies are excess monthly returns of the higher-illiquidity portfolios minus excess monthly returns of the lower-illiquidity portfolios.

There are three long strategies: buying stocks in the low-illiquidity portfolio (LIlliq), the medium-illiquidity portfolio (MIlliq), and the high-illiquidity portfolio (HIlliq). Table 7.6 shows that all excess monthly returns of long strategies are positive and significant at a 5 per cent level for the Milliq portfolio and a 1 per cent level for the Lilliq and Hilliq portfolios. In addition, these returns outperform the market because all alphas are positive and significant at a 1 per cent level. However, the return of the MIlliq portfolio (approximately 1.53%) is higher than those of the LIlliq portfolio (approximately 1.39%) and the HIlliq portfolio (approximately 1.48%). Therefore, for long strategies, buying stocks in the MIlliq portfolio earns a higher return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the high-illiquidity portfolio and selling stocks in the low-illiquidity portfolio (HIlliq–LIlliq), buying stocks in the high-illiquidity portfolio and selling stocks in the medium-illiquidity portfolio (HIlliq–MIlliq), buying stocks in the medium-illiquidity portfolio and selling stocks in the low-illiquidity portfolio (MIlliq–LIlliq). Table 7.6 shows that the returns of all these strategies are insignificant (indifferent from zero) and they are predicted by the market (all alphas are insignificant). Therefore, none of the arbitrage strategies earn a positive return. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on illiquidity, investors should buy stocks in the MIlliq portfolio to maximise the excess monthly return. This long strategy not only generates the highest excess monthly return (approximately 1.53%), but this return also outperforms the market (the alpha is approximately 1.38% monthly).

7.2.7. CAPM Beta Portfolios and Strategies

Table 7.7: CAPM Beta Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Higher CAPM Beta – Lower CAPM Beta)		
	LCAPM	**MCAPM**	**HCAPM**	**HCAPM–LCAPM**	**HCAPM–MCAPM**	**MCAPM–LCAPM**
Monthly Returns (%)	1.360	1.408	1.128	−0.232	−0.281	0.048
	t = 2.923* **	**t = 2.105** **	t = 1.533	t = −0.312	t = −0.564	t = 0.077
Monthly Alphas (%)	1.409	1.377	1.003	−0.406	−0.374	−0.032
	t = 3.193* **	**t = 2.871*** **	**t = 3.084*** **	t = −0.794	t = −0.807	t = −0.066

Notes: Returns and alphas are computed for three CAPM beta portfolios and the difference returns between higher-CAPM beta and lower CAPM beta portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

Table 7.7 shows the average monthly returns and alphas of long and arbitrage strategies based on CAPM beta from January 2011 to December 2019. Stocks are sorted into three CAPM-Beta portfolios (LCAPM, MCAPM, and HCAPM) using the 30th and 70th percentiles breakpoints of the CAPM beta. Based on the hypothesis that stock returns are positively correlated with CAPM beta, returns of higher-CAPM beta stocks should be higher than returns of lower-CAPM beta stocks. Therefore, arbitrage strategies that buy higher-CAPM beta stocks and sell lower-CAPM beta stocks should have positive returns. The returns of long strategies are excess monthly returns of the three CAPM-Beta portfolios. The returns of arbitrage strategies are excess monthly returns of the higher-CAPM beta portfolios minus excess monthly returns of the lower-CAPM beta portfolios.

There are three long strategies: buying stocks in the low-CAPM beta portfolio (LCAPM), the medium-CAPM beta portfolio (MCAPM), and the high-CAPM beta portfolio (HCAPM). Table 7.7 shows that although the excess monthly return of the HCAPM portfolio outperforms the market (the alpha is positive and significant at a 1% level), this return is insignificant (indifferent from zero). Both excess returns of the LCAPM and MCAPM portfolios are positive and significant at 5 per cent and 1 per cent levels, respectively. In addition, these returns outperform the market (the alphas are positive and significant at a 1% level). However, the excess monthly return of the MCAPM portfolio (approximately 1.41%) is higher than that of the LCAPM portfolio (approximately 1.36%). Therefore, for long strategies, buying stocks in the MCAPM portfolio earns a higher return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the high-CAPM beta portfolio and selling stocks in the low-CAPM beta portfolio (HCAPM–LCAPM), buying stocks in the high-CAPM beta portfolio and selling stocks in the medium-CAPM beta portfolio (HCAPM–MCAPM), buying stocks in the medium-CAPM beta portfolio and selling stocks in the low-CAPM beta portfolio (MCAPM–LCAPM). Table 7.7 shows that the monthly returns of all these strategies are insignificant (indifferent from zero) and they are predicted by the market (all alphas are insignificant). Therefore, none of the arbitrage strategies earn a positive return. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on CAPM beta, investors should buy stocks in the MCAPM portfolio to maximise the excess monthly return. This long strategy not only generates the highest excess monthly return (approximately 1.41%), but this return also outperforms the market (the alpha is approximately 1.38% monthly).

7.2.8. DCC Beta Portfolios and Strategies

Table 7.8 shows the average monthly returns and alphas of long and arbitrage strategies based on DCC beta from January 2011 to December 2019. Stocks are sorted into three DCC-Beta portfolios (LDCC, MDCC, and HDCC) using the 30th and 70th percentiles breakpoints of the DCC. Based on the hypothesis that stock returns are positively correlated with DCC beta, returns of higher-DCC beta stocks should be higher than returns of lower-DCC beta stocks. Therefore, arbitrage strategies that buy higher-DCC beta stocks and sell lower-DCC beta stocks should have positive returns. The returns of long strategies are excess monthly returns of the three DCC-Beta portfolios. The returns of arbitrage strategies are excess monthly returns of the higher-DCC beta portfolios minus excess monthly returns of the lower-DCC beta portfolios.

Table 7.8: DCC Beta Portfolios and Strategies

Strategies / Returns/Alphas	Long Strategies			Arbitrage Strategies (Higher DCC Beta – Lower DCC Beta)		
	LDCC	**MDCC**	**HDCC**	**HDCC–LDCC**	**HDCC–MDCC**	**MDCC–LDCC**
Monthly Returns (%)	1.086	1.763	1.093	0.007	−0.670	0.678
	t = 3.322* **	**t = 3.735*** **	t = 1.568	t = 0.013	t = −0.964	t = 1.295
Monthly Alphas (%)	0.912	1.865	1.057	0.145	−0.808	0.952
	t = 3.266* **	**t = 3.776*** **	**t = 4.061*** **	t = 0.506	t = −1.610	**t = 2.335** **

Notes: Returns and alphas are computed for three DCC beta portfolios and the difference returns between higher-DCC beta and lower DCC beta portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

There are three long strategies: buying stocks in the low-DCC beta portfolio (LDCC), the medium-DCC beta portfolio (MDCC), and the high-DCC beta portfolio (HDCC). Although the excess monthly return of the HCAPM portfolio outperforms the market (the alpha is positive and significant at a 1% level), this return is insignificant (indifferent from zero). Both excess monthly returns of the LDCC and MDCC portfolios are positive and significant at 5 per cent and 1 per cent levels, respectively. In addition, these returns outperform the market (the alphas are positive and significant at a 1 per cent level. However, the excess monthly return of the MDCC portfolio (approximately 1.76%) is higher than that of the LDCC portfolio (approximately 1.09%). Therefore, for long strategies, buying stocks in the MDCC portfolio earns a higher return than the others and this return also outperforms the market.

There are three arbitrage strategies: buying stocks in the high-DCC beta portfolio and selling stocks in the low-DCC beta portfolio (HDCC–LDCC), buying stocks in the high-DCC beta portfolio and selling stocks in the medium-DCC beta portfolio (HDCC–MDCC), buying stocks in the medium-DCC beta portfolio and selling stocks in the low-DCC beta portfolio (MDCC–LDCC). The monthly returns of the DHCC–LDCC and HDCC–MDCC portfolios are insignificant (indifferent from zero). These returns are also predicted by the market (the alphas are insignificant). Although the return of the MDCC–LDCC portfolio outperforms the market, this return is insignificant (indifferent from zero). Therefore, none of the arbitrage strategies earn a positive return. Furthermore, short selling is not allowed in the Vietnamese stock market currently. Hence, for stock selection based on DCC beta, investors should buy stocks in the MDCC portfolio to maximise the excess monthly return. This long strategy not only generates the highest excess monthly return (approximately 1.76%), but this return also outperforms the market (the alpha is approximately 1.87% monthly).

7.3. Double Sorts and Strategies

The tests using double sorting are similar to the tests using single sorting; however, the double sorting will enhance the test because this traces for efficient strategies in smaller groups (portfolios). Double sorting breaks the sample stocks into six portfolios using the size median breakpoint and 30th and 70th percentiles for other firm characteristics. The performance of long and arbitrage strategies is tested by nonparametric and parametric methods on portfolio returns. The nonparametric method uses a t-test. The parametric method uses alphas which are the intercepts of the regressions of returns of these long and arbitrage strategies on the returns of the MKT, SMB, and CMA factors. The details of the strategies are represented below.

7.3.1. Size–Value Portfolios and Strategies

Table 7.9 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and firm value from January 2011 to December 2019. Stocks are sorted into six Size–Value portfolios (SH, BH, SM, BM, SL, and BL) using the median breakpoint for the firm size and the 30th and 70th percentiles breakpoints for the firm value.

For long strategies, Table 7.9 shows six long strategies: buying stocks in the SH, BH, SM, BM, SL, and BL portfolios. Table 7.9 shows that both excess monthly returns and alphas of the SL and BM portfolios are insignificant (indifferent from zero). Although the strategies that buy stocks in the BH and BL portfolios outperform the market (the alphas are positive and significant at 10% and 1% levels, respectively), the returns of these strategies are not significant (indifferent from zero). Only the returns of the SH and SM portfolios are both positive and outperform the market. The alphas of the two portfolios are positive and significant at a 5 per cent level for the SH portfolio and a 1 per cent level for the SM portfolio. Similarly, their returns are positive and significant at a 10 per cent level for the SH portfolio and a 1 per cent level for the SM portfolio. However, the excess monthly return of the SM portfolio (approximately 1.61%) is higher than that of the SH portfolio (approximately 1.44%). Therefore, for long strategies, the strategy that buys stocks in the SM portfolio earns a higher return than the others and this return also outperforms the market.

Table 7.9: Size–Value Portfolios and Strategies

Panel A: Monthly Returns (%)

Value \ Size	Small (S)	Big (B)	S–B
High (H)	1.443	1.239	0.203
	t = 1.811*	t = 1.435	t = 0.391
Medium (M)	1.610	0.519	1.091
	t = 2.645***	t = 0.755	**t = 2.719*****
Low (L)	0.440	0.747	−0.307
	t = 0.733	t = 1.376	t = −0.441
H–L	1.003	0.492	
	t = 1.338	t = 0.644	
H–M	−0.167	0.720	
	t = −0.324	t = 1.266	
M–L	1.170	−0.227	
	t = 1.726*	t = −0.417	

Trading Strategies

Long strategies (grey)

Long smaller size – short bigger size (orange)

Long higher value – short lower value (yellow)

Panel B: Monthly Alphas (%)

Value \ Size	Small (S)	Big (B)	S–B
High (H)	0.828	1.045	−0.216
	t = 2.332**	**t = 1.860***	t = −0.414
Medium (M)	1.190	0.464	0.726
	t = 3.137***	t = 1.111	**t = 2.297****
Low (L)	0.112	0.839	−0.728
	t = 0.235	**t = 2.652*****	t = −1.567
H–L	0.717	0.205	
	t = 1.354	t = 0.386	
H–M	−0.362	0.581	
	t = −0.883	t = 1.028	
M–L	1.079	−0.375	
	t = 1.903*	t = −1.023	

Notes: Returns and alphas are computed for six Size–Value portfolios, the difference returns between smaller-size and bigger-size portfolios, and between higher-value and lower-value portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level.*

***Significant at the 5% level.*

**Significant at the 10% level.*

For arbitrage strategies based on the firm size, Table 7.9 shows three strategies that buy small-size and sell big-size stocks: one in the high-value portfolio (SH–BH), one in the medium-value portfolio (SM-BM), and one in the low-value portfolio (SL–BL). Both the returns and alphas of the SH–BH and SL–BL portfolios are insignificant (indifferent from zero). Only the return of the SM–BM portfolio is positive and outperforms the market. The alpha of this portfolio is positive and significant at a 5 per cent level. Similarly, the monthly return of the portfolio is positive (approximately 1.09%) and significant at a 1 per cent level. Therefore, for arbitrage strategies that buy small-size and sell big-size stocks, buying stocks in the SM portfolio and selling stock in the BM portfolio (SM–BM) outperforms the market and has a higher return than the others.

For arbitrage strategies based on the firm value, Table 7.9 shows six strategies that buy higher-value and sell lower-value stocks: three strategies in the small-size portfolio (SH–SL, SH–SM, SM–SL) and 3 strategies in the big-size portfolio (BH–BL, BH–BM, BM–BL). Both returns and alphas of the SH–SL, SH–SM, BH–BL, BH–BM, and BM–BL portfolios are insignificant. Only the return of the SM–SL portfolio is positive and outperforms the market. The alpha of this portfolio is positive and significant at a 10 per cent level. Similarly, the excess monthly return of this portfolio is positive (approximately 1.17%) and significant at a 10 per cent level. Therefore, for arbitrage strategies that buy higher-value and sell lower-value stocks, the strategy that buys stocks in the SM and sells stock in the SL (SM–SL) earns a higher return than the others and this return outperforms the market. The return of the SM–SL portfolio is also higher than that of the SM–BM portfolio. However, the returns of these arbitrage strategies are smaller than that of the long strategy (SM). In addition, the return of the SM portfolio outperforms the market. Therefore, investors should buy stocks in the SM portfolio to maximise the excess monthly return (approximately 1.61%).

7.3.2. Size–Momentum Portfolios and Strategies

Table 7.10 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and momentum from January 2011 to December 2019. Stocks are sorted into six Size–Momentum portfolios (SU, BU, SN, BN, SD, and BD) using the median breakpoint of the firm size and the 30th and 70th percentiles breakpoints of the momentum.

For long strategies, Table 7.10 shows six long strategies: buying stocks in the SU, BU, SN, BN, SD, and BD portfolios. Both returns and alphas of SD, BN, and BD portfolios are insignificant (indifferent from zero). Although the strategy that buys stocks in the BU portfolio outperforms the market (the alphas are positive and significant at a 10% level), the return of this strategy is not significant (indifferent from zero). Only the returns of the SU and SN portfolios are both positive and outperform the market. The alphas and returns of the two portfolios are positive and significant at a 1 per cent level. However, the excess monthly return of the SU portfolio (approximately 1.94%) is higher than that of the SN portfolio (approximately 1.37%). Therefore, for long strategies, the strategy that buys stocks in the SU portfolio earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on the firm size, Table 7.10 shows three strategies that buy small-size and sell big-size stocks: one in the up-momentum portfolio (SU–BU), one in the neutral-momentum portfolio (SN–BN), and one in the down-momentum portfolio (SD–BD). Both the return and alpha of the SN–BN portfolio are insignificant (indifferent from zero). The excess monthly return of the SU–BU portfolio (approximately 1.17%) is higher than that of the SD–BD portfolio (approximately 1.04%). Both returns are significant at a 10 per cent level. These returns are predicted by the market because their alphas are insignificant (indifferent from zero). Therefore, for arbitrage strategies that buy small-size and sell big-size stocks, the return of the strategy that buys stocks in the SU portfolio and sells stock in the BU portfolio (SU–BU) is predicted by the market and has a higher return than the others.

Table 7.10: Size–Momentum Portfolios and Strategies

Panel A: Monthly Returns (%)			
Momentum \ Size	**Small (S)**	**Big (B)**	**S–B**
Up (U)	1.941	0.766	1.174
	t = 2.890***	t = 1.404	**t = 1.886***
Neutral (N)	1.366	0.582	0.783
	t = 2.659***	t = 0.924	t = 1.459
Down (D)	0.792	−0.244	1.036
	t = 0.910	t = −0.416	**t = 1.753***
U–D	1.149	1.011	*Trading Strategies*
	t = 1.764*	t = 1.444	*Long strategies*
U–N	0.575	0.184	*Long smaller size – short bigger size*
	t = 1.300	t = 0.357	*Long higher momentum – short lower momentum*
N–D	0.574	0.827	
	t = 0.970	**t = 1.908***	

Panel B: Monthly Alphas (%)			
Momentum \ Size	**Small (S)**	**Big (B)**	**S–B**
Up (U)	1.599	0.872	0.727
	t = 3.272***	**t = 1.842***	t = 1.465
Neutral (N)	0.967	0.580	0.387
	t = 3.403***	t = 1.361	t = 1.135
Down (D)	0.163	−0.340	0.503
	t = 0.345	t = −0.818	t = 1.227
U–D	1.436	1.212	*Notes: Returns and alphas are computed for six Size–Momentum portfolios, the difference returns between smaller-size and bigger-size portfolios, and between higher-momentum and lower-momentum portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).*
	t = 2.439**	**t = 1.867***	
U–N	0.633	0.293	
	t = 1.387	t = 0.532	****Significant at the 1% level.*
N–D	0.803	0.920	***Significant at the 5% level.*
	t = 1.558	**t = 2.118****	**Significant at the 10% level.*

For arbitrage strategies based on momentum, Table 7.10 shows six strategies that buy higher-momentum and sell lower-momentum stocks: three strategies in the small-size portfolio (SU–SD, SU–SN, SN–SD) and 3 strategies in the big-size portfolio (BU–BD, BU–BN, BN–BD). Both returns and alphas of the SU–SN, SN–SD, and BU–BN portfolios are insignificant (indifferent from zero). Although the return of the BU–BD portfolio outperforms the market (the alpha is positive and significant at a 10% level), the return of this portfolio is insignificant (indifferent from zero). Only the returns of the SU–SD and BN–BD portfolios are positive and outperform the market. The alphas of these portfolios are positive and significant at a 5 per cent level. Similarly, the excess monthly returns of the two portfolios are significant at a 10 per cent level. However, the return of the SU–SD portfolio (approximately 1.15%) is higher than that of the BN–BD portfolio (approximately 0.83%). Therefore, for arbitrage strategies that buy higher-momentum and sell lower-momentum stocks, the strategy that buys stocks in the SU portfolio and sells stock in the SD portfolio (SU–SD) outperforms the market and has a higher return than the others. The return of the SU–SD portfolio is lower than that of the SU–BU. However, the returns of these arbitrage strategies are smaller than that of the long strategy (SU). In addition, the return of the SU portfolio outperforms the market. Therefore, investors should buy stocks in the SU portfolio to maximise the excess monthly return (approximately 1.94%).

7.3.3. Size–VaR Portfolios and Strategies

Table 7.11 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and Value-at-Risk (VaR) from January 2011 to December 2019. Stocks are sorted into six Size–VaR portfolios (SHVaR, BHVaR, SMVaR, BMVaR, SLVaR, and BLVaR) using the median breakpoint of the firm size and the 30th and 70th percentiles breakpoints of the VaR.

Table 7.11: Size–VaR Portfolios and Strategies

Panel A: Monthly Returns (%)			
VaR \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HVaR)	2.382	0.028	2.355
	t = 2.560**	t = 0.038	**t = 3.665*****
Medium (MVaR)	0.617	0.859	−0.242
	t = 1.125	t = 1.241	t = −0.510
Low (LVaR)	0.929	0.610	0.319
	t = 2.043**	t = 1.056	t = 0.473
HVaR–LVaR	1.453	−0.582	
	t = 1.896*	t = −0.675	
HVaR–MVaR	1.765	−0.832	
	t = 3.018***	t = −1.372	
MVaR–LVaR	−0.312	0.250	
	t = −0.806	t = 0.381	
Panel B: Monthly Alphas (%)			
VaR \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HVaR)	1.716	−0.16	1.876
	t = 3.879***	t = −0.311	**t = 3.236*****
Medium (MVaR)	0.234	0.855	−0.621
	t = 0.645	**t = 2.189****	**t = −2.001****
Low (LVaR)	0.633	0.752	−0.119
	t = 2.053**	**t = 1.973***	t = −0.289
HVaR–LVaR	1.083	−0.912	
	t = 1.970*	t = −1.505	
HVaR–MVaR	1.482	−1.015	
	t = 3.614***	**t = −1.704***	
MVaR–LVaR	−0.399	0.103	
	t = −1.174	t = 0.218	

Trading Strategies

- *Long strategies*
- *Long smaller size – short bigger size*
- *Long higher VaR – short lower VaR*

Notes: Returns and alphas are computed for six Size–VaR portfolios, the difference returns between smaller-size and bigger-size portfolios, and between higher-VaR and lower-VaR portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey & West (1987).

****Significant at the 1% level.*

***Significant at the 5% level.*

**Significant at the 10% level.*

For long strategies, Table 7.11 shows six long strategies: buying stocks in the SHVaR, BHVaR, SMVaR, BMVaR, SLVaR, and BLVaR portfolios. Both returns and alphas of SMVaR and BHVaR are insignificant (indifferent from zero). Although the strategies that buy stocks in the

BMVaR and BLVaR portfolios outperform the market (the alphas are positive and significant at 5% and 10% levels, respectively), the returns of these strategies are not significant (indifferent from zero). Only the returns of the SHVaR and SLVaR portfolios are both positive and outperform the market. The alphas of the two portfolios are positive and significant at a 1 per cent level for the SHVaR portfolio and a 5 per cent level for the SLVaR portfolio. Similarly, their returns are positive and significant at a 5 per cent level. However, the excess monthly return of the SHVaR portfolio (approximately 2.38%) is higher than that of the SLVaR portfolio (approximately 0.93%). Therefore, for long strategies, the strategy that buys stocks in the SHVaR portfolio earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on the firm size, Table 7.11 shows three strategies that buy small-size and sell big-size stocks: one in the high-VaR portfolio (SHVaR–BHVaR), one in the medium-VaR portfolio (SMVaR–BMVaR), and one in the low-VaR portfolio (SLVaR–BLVaR). Both the return and alpha of the SLVaR–BLVaR portfolio are insignificant (indifferent from zero). Although the return of the SMVaR–BMVaR portfolio underperforms the market (the alpha of this portfolio is negative and significant at a 5% level), the excess monthly return of the portfolio is insignificant (indifferent from zero). Only the return of the SHVaR–BHVaR portfolio is positive and outperforms the market. The alpha of this portfolio is positive and significant at a 1 per cent level. Similarly, the excess monthly return of the SHVaR–BHVaR portfolio is positive (approximately 2.36 percent) and significant at a 1 per cent level. Therefore, for arbitrage strategies that buy small-size and sell big-size stocks, the strategy that buys stocks in the SHVaR and sells stock in the BHVaR (SHVaR–BHVaR) earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on the Value-at-Risk (VaR), Table 7.11 shows six strategies that buy higher-VaR and sell lower-VaR stocks: three strategies in the small-size portfolio (SHVaR–SLVaR, SHVaR–SMVaR, SMVaR–SLVaR) and three strategies in the big-size portfolio (BHVaR–BLVaR, BHVaR–BMVaR, BMVaR–BLVaR). Both returns and alphas of the BHVaR–BLVaR, SMVaR–SLVaR, and BMVaR–BLVaR portfolios are insignificant (indifferent from zero). Although the return of the BHVaR–BMVaR portfolio underperforms the market (the alpha of this portfolio is negative and significant at a 10% level), the return of this portfolio is insignificant (indifferent from zero). Only returns of the SHVaR–SLVaR and SHVaR–SMVaR portfolios are positive and outperform the market. The alphas of these portfolios are positive and significant at a 10 per cent level for the SHVaR–SLVaR portfolio and a 1 per cent level for the SHVaR–SMVaR portfolio. Similarly, the excess monthly returns of these portfolios are significant at 10 per cent and 1 per cent levels, respectively. However, the return of the SHVaR–SMVaR portfolio (approximately 1.77%) is higher than that of the SHVaR–SLVaR portfolio (approximately 1.45%). Therefore, for arbitrage strategies that buy higher-VaR and sell lower-VaR stocks, the strategy that buys stocks in the SHVaR and sells stock in the SMVaR (SHVaR–SMVaR) earns a higher return than the others and this return outperforms the market. The return of the SHVaR–SMVaR portfolio is lower than that of the SHVaR–BHVaR portfolio. However, the returns of these arbitrage strategies are smaller than that of the long strategy (SHVaR). In addition, the return of the SHVaR portfolio outperforms the market. Therefore, investors should buy stocks in the SHVaR portfolio to maximise the excess monthly return (approximately 2.38%).

7.3.4. Size–CVaR Portfolios and Strategies

Table 7.12 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and conditional Value-at-Risk (CVaR) from January 2011 to December 2019. Stocks are sorted into six Size–CVaR portfolios (SHCVaR, BHCVaR, SMCVaR, BMCVaR, SLCVaR, and BLCVaR) using the median breakpoint of the firm size and the 30th and 70th percentiles breakpoints of the CVaR.

Table 7.12: Size–CVaR Portfolios and Strategies

Panel A: Monthly Returns (%)			
CVaR \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HCVaR)	2.067	0.050	2.017
	t = 2.354**	t = 0.082	**t = 3.238*****
Medium (MCVaR)	1.044	0.418	0.626
	t = 1.647	t = 0.608	t = 1.474
Low (LCVaR)	0.844	1.089	−0.244
	t = 1.724*	**t = 1.846***	t = −0.354
LCVaR–HCVaR	−1.223	1.038	*Trading Strategies*
	t = −1.640	t = 1.358	*Long strategies*
MCVaR–HCVaR	−1.024	0.367	*Long smaller size – short bigger size*
	t = −2.000**	t = 0.784	*Long lower CVaR – short higher CVaR*
LCVaR–MCVaR	−0.199	0.671	
	t = −0.414	t = 0.979	
Panel B: Monthly Alphas (%)			
CVaR \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HCVaR)	1.413	−0.042	1.454
	t = 3.301***	t = −0.103	**t = 2.971*****
Medium (MCVaR)	0.685	0.418	0.267
	t = 1.778*	t = 1.113	t = 0.797
Low (LCVaR)	0.468	1.172	−0.704
	t = 1.333	**t = 3.130*****	**t = −1.936***
LCVaR–HCVaR	−0.944	1.214	*Notes: Returns and alphas are computed for six Size–CVaR portfolios, the difference returns between smaller-size and bigger-size portfolios, and between lower-CVaR and higher-CVaR portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).*
	t = −1.860*	**t = 2.262****	
MCVaR–HCVaR	−0.727	0.46	
	t = −1.700*	t = 1.003	****Significant at the 1% level.*
LCVaR–MCVaR	−0.217	0.754	***Significant at the 5% level.*
	t = −0.539	**t = 1.747***	**Significant at the 10% level.*

For long strategies, Table 7.12 shows six long strategies: buying stocks in the SHCVaR, BHCVaR, SMCVaR, BMCVaR, SLCVaR, and BLCVaR portfolios. Both returns and alphas of BHCVaR and BMCVaR are insignificant (indifferent from zero). Although the strategy that buys stocks in the BMCVaR portfolio outperforms the market (the alpha is positive and significant at a 10% level), the return of this strategy is not significant (indifferent from zero). Only the returns of the SHCVaR and BLCVaR portfolios are both positive and outperform the market. The alphas of the two portfolios are positive and significant at a 1 per cent level. Similarly, their returns are positive and significant at a 5 per cent level for the SHCVaR portfolio and a 10 per cent level for the BLCVaR portfolio. However, the excess monthly return of the SHCVaR portfolio (approximately 2.07%) is higher than that of the BLCVaR portfolio (approximately 1.09%). Therefore, for long strategies, the strategy that buys stocks in the SHCVaR portfolio earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on the firm size, Table 7.12 shows three strategies that buy small-size and sell big-size stocks: one in the high-CVaR portfolio (SHCVaR–BHCVaR), one in the medium-CVaR portfolio (SMCVaR–BMCVaR), and one in the low-CVaR portfolio (SLCVaR–BLCVaR). Both the return and alpha of the SMCVaR–BMCVaR portfolio are insignificant (indifferent from zero). Although the return of the LCVaR–BLCVaR portfolio underperforms the market (the alpha of this portfolio is negative and significant at a 10% level), the return of the portfolio is insignificant (indifferent from zero). Only the return of the SHCVaR–BHCVaR portfolio is positive and outperforms the market. The alpha of this portfolio is positive and significant at a 1 per cent level. Similarly, the excess monthly return of the portfolio (approximately 2.02%) is significant at a 1 per cent level. Therefore, for arbitrage strategies that buy small-size and sell big-size stocks, the strategy that buys stocks in the SHCVaR and sells stock in the BHCVaR (SHCVaR–BHCVaR) earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on the conditional Value-at-Risk (CVaR), Table 7.12 shows six arbitrage strategies that buy lower-CVaR and sell higher-CVaR stocks: three strategies in the small-size portfolio (SLCVaR–SHCVaR, SMCVaR–SHCVaR, SLCVaR–SMCVaR) and three strategies in the big-size portfolio (BLCVaR–BHCVaR, BMCVaR–BHCVaR, BLCVaR–BMCVaR). Both returns and alphas of SLCVaR–SMCVaR and BMCVaR–BHCVaR portfolios are insignificant (indifferent from zero). In contrast, the SLCVaR–SHCVaR and SMCVaR–SHCVaR portfolios underperform the market. The alphas of these portfolios are negative and significant at a 10 per cent level. Both the excess monthly returns are also negative; however, only the return of the SMCVaR–SHCVaR portfolio (approximately -1.02% monthly) is significant at a 5 per cent level. While the BLCVaR–BHCVaR and BLCVaR–BMCVaR portfolios outperform the market (the alphas are positive and significant at 5% and 10% levels, respectively), their returns are insignificant (indifferent from zero). Therefore, none of the arbitrage strategies that buy lower-CVaR and sell higher-CVaR stocks earn a positive return. Hence, only the return of the arbitrage strategy (SHCVaR–BHCVaR) is positive and significant. However, this return is smaller than that of the long strategy (SHCVaR). In addition, the return of the SHCVaR portfolio outperforms the market. Therefore, investors should buy stocks in the SHCVaR portfolio to maximise the excess monthly return (approximately 2.07%).

7.3.5. Size–Illiquidity Portfolios and Strategies

Table 7.13 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and illiquidity from January 2011 to December 2019. Stocks are sorted into six Size–Illiquidity portfolios (SHIlliq, BHIlliq, SMIlliq, BMIlliq, SLIlliq, and BLIlliq) using the median breakpoint of the firm size and the 30th and 70th percentiles breakpoints of the illiquidity.

Table 7.13: Size–Illiquidity Portfolios and Strategies

Illiquidity \ Size	Small (S)	Big (B)	S–B
Panel A: Monthly Returns (%)			
High (HIlliq)	1.539	0.049	1.490
	t = 2.864* **	t = 0.101	**t = 3.056*** **
Medium (MIlliq)	1.390	0.661	0.729
	t = 1.909*	t = 1.203	**t = 1.764***
Low (LIlliq)	0.667	0.752	−0.085
	t = 0.493	t = 1.363	t = −0.066
HIlliq–LIlliq	0.871	−0.703	
	t = 0.764	t = −1.279	
HIlliq–MIlliq	0.149	−0.612	
	t = 0.279	t = −1.419	
MIlliq–LIlliq	0.722	−0.092	
	t = 0.595	t = −0.194	
Panel B: Monthly Alphas (%)			
High (HIlliq)	1.038	0.038	1
	t = 3.050* **	t = 0.090	**t = 2.432** **
Medium (MIlliq)	0.961	0.528	0.433
	t = 2.500 **	t = 1.208	t = 1.221
Low (LIlliq)	−0.165	0.824	−0.989
	t = −0.158	**t = 2.765*** **	t = −0.928
HIlliq–LIlliq	1.203	−0.786	
	t = 1.175	**t = −1.979***	
HIlliq–MIlliq	0.077	−0.49	
	t = 0.198	t = −1.110	
MIlliq–LIlliq	1.126	−0.296	
	t = 1.027	t = −1.023	

Trading Strategies

Long strategies

Long smaller-size – short bigger-size

Long higher-illiquid – short lower-illiquid

Notes: Returns and alphas are computed for six Size–Illiquidity portfolios, the difference returns between smaller-size and bigger-size portfolios, and between higher-illiquidity and lower-illiquidity portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level.*

***Significant at the 5% level.*

**Significant at the 10% level.*

For long strategies, Table 7.13 shows six long strategies: buying stocks in the SHIlliq, BHIlliq, SMIlliq, BMIlliq, SLIlliq, and BLIlliq portfolios. Both returns and alphas of BHIlliq, BMIlliq, and SLIlliq portfolios are insignificant (indifferent from zero). Although the strategy that buys stocks in the BLIlliq portfolio outperforms the market (the alpha is positive and significant at a 1% level), the return of this strategy is not significant (indifferent from zero). Only the returns of the SHIlliq and SMIlliq portfolios are both positive and outperform the market. The alphas of the two portfolios are positive and significant at a 1 per cent level for the SHIlliq portfolio and a 5 per cent level for the SMIlliq portfolio. Similarly, their returns are positive and significant at a 1 per cent level for the SHIlliq portfolio and a 10 per cent level for the SMIlliq portfolio. However, the excess monthly return of the SHIlliq portfolio (approximately 1.54%) is higher than that of the SIlliq portfolio (approximately 1.39%). Therefore, for long strategies, the strategy that buys stocks in the SHIlliq portfolio earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on the firm size, Table 7.13 shows three strategies that buy small-size and sell big-size stocks: one in the high-illiquid portfolio (SHIlliq–BHIlliq), one in the medium-illiquid portfolio (SMIlliq–BMIlliq), and one in the low-illiquid portfolio (SLIlliq–BLlliq). Both the return and alpha of the SLIlliq–BLIlliq portfolio are insignificant (indifferent from zero). In contrast, the return of the SMIlliq–BMIlliq is positive and significant at a 10 per cent level. This return is predicted by the market because the alpha of the portfolio is insignificant. Only the return of the SHIlliq–BHIlliq portfolio is positive and outperforms the market. The alpha of this portfolio is positive and significant at a 5 per cent level. Similarly, the excess monthly return of the portfolio is positive (approximately 1.49%) and significant at a 1 per cent level. Therefore, for arbitrage strategies that buy small-size and sell big-size stocks, the strategy that buys stocks in the SHIlliq and sells stock in the BHIlliq (SHIlliq–BHIlliq) earns a higher return than the others and this return outperforms the market.

For arbitrage strategies based on illiquidity, Table 7.13 shows six strategies that buy higher-illiquid and sell lower-illiquid stocks: three strategies in the small-size portfolio (SHIlliq–

SLIlliq, SHIlliq–SMIlliq, SMIlliq–SLIlliq) and 3 strategies in the big-size portfolio (BHIlliq–BLIlliq, BHIlliq–BMIlliq, BMIlliq–BLIlliq). Both returns and alphas of the 5 portfolios (SHIlliq–SLIlliq, SHIlliq–SMIlliq, SMIlliq–SLIlliq, BHIlliq–BMIlliq, and BMIlliq–BLIlliq) are insignificant (indifferent from zero). In addition, the return of the BHIlliq–BLIlliq portfolio underperforms the market (the alpha is negative and significant at a 10% level). However, the return of this portfolio is insignificant. Therefore, none of the arbitrage strategies that buy higher-illiquid and sell lower-illiquid stocks earn a positive return. Hence, only the return of the arbitrage strategy (SHIlliq–BHIlliq) is positive and significant. However, this return is smaller than that of the long strategy (SHIlliq). In addition, the return of the SHIlliq portfolio outperforms the market. Therefore, investors should buy stocks in the SHIlliq portfolio to maximise the excess monthly return (approximately 1.54%).

7.3.6. Size–CAPM Beta Portfolios and Strategies

Table 7.14 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and CAPM beta from January 2011 to December 2019. Stocks are sorted into six Size–CAPM beta portfolios (SHCAPM, BHCAPM, SMCAPM, BMCAPM, SLCAPM, and BLCAPM) using the median breakpoint of the firm size and the 30th and 70th percentiles breakpoints of the CAPM beta.

For long strategies, Table 7.14 shows six long strategies: buying stocks in the SHCAPM, BHCAPM, SMCAPM, BMCAPM, SLCAPM, and BLCAPM portfolios. Both returns and alphas of the four portfolios (BHCAPM, SMCAPM, BMCAPM, and BLCAPM) are insignificant (indifferent from zero). Although the strategy that buys stocks in the SHCAPM portfolio outperforms the market (the alpha is positive and significant at a 10% level), the return of this strategy is not significant (indifferent from zero). Only the return of the SLCAPM portfolio is both positive and outperforms the market. The alpha of this portfolio is positive and significant at a 1 per cent level. Similarly, its excess monthly return is positive (approximately 1.61%) and significant at a 1 percent level. Therefore, for long strategies, the strategy that buys stocks in the SLCAPM earns a higher return than the others and this return outperforms the market.

Table 7.14: Size–CAPM Beta Portfolios and Strategies

Panel A: Monthly Returns (%)			
CAPM Beta \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HCAPM)	1.501	0.480	1.021
	t = 1.597	t = 0.618	t = 1.627
Medium (MCAPM)	1.018	0.725	0.293
	t = 1.657	t = 1.071	t = 0.572
Low (LCAPM)	1.611	0.546	1.065
	t = 2.923****	t = 1.133	t = 1.525
HCAPM–LCAPM	−0.110	−0.066	*Trading Strategies*
	t = −0.141	t = −0.078	*Long strategies* (grey)
HCAPM–MCAPM	0.483	−0.245	*Long smaller-size – short bigger-size* (orange)
	t = 0.731	t = −0.486	*Long higher-CAPM beta – short lower-CAPM beta* (yellow)
MCAPM–LCAPM	−0.593	0.179	
	t = −1.321	t = 0.249	
Panel B: Monthly Alphas (%)			
CAPM Beta \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HCAPM)	0.896	0.361	0.535
	t = 1.895*	t = 1.203	t = 1.261
Medium (MCAPM)	0.577	0.722	−0.144
	t = 1.579	t = 1.452	t = −0.307
Low (LCAPM)	1.138	0.642	0.496
	t = 3.053****	t = 1.344	t = 0.955
HCAPM–LCAPM	−0.242	−0.281	*Notes: Returns and alphas are computed for six Size–CAPM beta portfolios, the difference returns between smaller-size and bigger-size portfolios, and between higher-CAPM beta and lower-CAPM beta portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).*
	t = −0.439	t = −0.516	
HCAPM–MCAPM	0.319	−0.361	
	t = 0.631	t = −0.739	****Significant at the 1% level.*
MCAPM–LCAPM	−0.561	0.08	***Significant at the 5% level.*
	t = −1.171	t = 0.142	**Significant at the 10% level.*

For arbitrage strategies based on the firm size, Table 7.14 shows three strategies that buy small-size and sell big-size stocks: one in the high-CAPM beta portfolio (SHCAPM–BHCAPM), one in the medium-CAPM beta portfolio (SMCAPM–BMCAPM), and one in the low-illiquid portfolio (SLCAPM–BLCAPM). Both the returns and alphas of these three portfolios are insignificant (indifferent from zero). Therefore, none of the arbitrage strategies that buy small-size and sell big-size stocks earn a positive return.

For arbitrage strategies based on CAPM beta, Table 7.14 shows six strategies that buy higher-CAPM beta and sell lower-CAPM beta stocks: three strategies in the small-size portfolio (SHCAPM–SLCAPM, SHCAPM–SMCAPM, SMCAPM–SLCAPM) and 3 strategies in the big-size portfolio (BHCAPM–BLCAPM, BHCAPM–BMCAPM, BMCAPM–BLCAPM). Both returns and alphas of these six portfolios are insignificant (indifferent from zero). Therefore, none of the arbitrage strategies that buy higher-CAPM beta and sell lower-CAPM beta stocks earn a positive return. While none of the returns of the arbitrage strategies is indifferent from zero, the return of the long strategy (SLCAPM) is positive and outperforms the market. Therefore, investors should buy stocks in the SLCAPM portfolio to maximise the excess monthly return (approximately 1.61%).

7.3.7. Size–DCC Beta Portfolios and Strategies

Table 7.15 shows the average monthly returns and alphas of long and arbitrage strategies based on firm size and firm value from January 2011 to December 2019. Stocks are sorted into six Size–DCC beta portfolios (SHDCC, BHDCC, SMDCC, BMDCC, SLDCC, and BLDCC) using the median breakpoint of the firm size and the 30th and 70th percentiles breakpoints of the DCC beta.

Table 7.15: Size–DCC Beta Portfolios and Strategies

Panel A: Monthly Returns (%)			
DCC Beta \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HDCC)	1.447	0.428	1.019
	t = 1.299	t = 0.592	t = 1.406
Medium (MDCC)	1.053	1.125	−0.073
	t = 1.506	**t = 2.300****	t = −0.105
Low (LDCC)	1.417	0.013	1.404
	t = 2.824***	t = 0.035	**t = 2.623*****
HDCC–LDCC	0.030	0.415	*Trading Strategies*
	t = 0.031	t = 0.590	*Long strategies* (grey)
HDCC–MDCC	0.394	−0.697	*Long smaller size – short bigger size* (orange)
	t = 0.574	t = −0.931	*Long higher-DCC beta – short lower-DCC beta* (yellow)
MDCC–LDCC	−0.364	1.112	
	t = −0.570	**t = 2.055****	

Panel B: Monthly Alphas (%)			
DCC Beta \ Size	**Small (S)**	**Big (B)**	**S–B**
High (HDCC)	−0.08	0.821	0.406
	t = −0.142	t = 1.492	**t = 1.672***
Medium (MDCC)	−0.416	0.696	1.254
	t = −0.903	**t = 1.703***	**t = 2.594****
Low (LDCC)	0.558	0.952	−0.055
	t = 1.528	**t = 2.557****	t = −0.155
HDCC–LDCC	−1.007	−0.131	
	t = −2.193**	t = −0.209	
HDCC–MDCC	0.461	0.126	
	t = 1.335	t = 0.223	
MDCC–LDCC	−0.848	−0.257	
	t = −1.661*	t = −0.563	

Notes: Returns and alphas are computed for six Size–DCC beta portfolios, the difference returns between smaller-size and bigger-size portfolios, and between higher-DCC beta and lower-DCC beta portfolios from January 2011 to December 2019. The standard errors are robust using the method developed by Newey and West (1987).

****Significant at the 1% level.*

***Significant at the 5% level.*

**Significant at the 10% level.*

For long strategies, Table 7.15 shows six long strategies: buying stocks in the SHDCC, BHDCC, SMDCC, BMDCC, SLDCC, and BLDCC portfolios. Both returns and alphas of SHDCC, BHDCC, and SMDCC portfolios are insignificant (indifferent from zero). Although the strategy that buys stocks in the BLDCC portfolio outperforms the market (the alpha is positive and significant at a 5% level), the return of this strategy is not significant (indifferent from zero). In contrast, the excess monthly return of the strategy that buys stocks in the SLDCC portfolio is positive (approximately1.42%) and significant at a 1 per cent level. This return is predicted by the market because the alpha is insignificant and indifferent from zero. Only the return of the BMDCC portfolio is both positive and outperforms the market. The alpha of this portfolio is positive and significant at a 10 per cent level. Similarly, its excess monthly return is positive (approximately 1.13%) and significant at a 5 per cent level. However, the excess monthly return of the BMDCC portfolio is lower than that of the SLDCC portfolio. Therefore, for long strategies, the strategy that buys stocks in the SLDCC portfolio earns a higher return than the others. This return is predicted by the market.

For arbitrage strategies based on the firm size, Table 7.15 shows three strategies that buy small-size and sell big-size stocks: one in the high-DCC portfolio (SHDCC–BHDCC), one in the medium-DCC portfolio (SMDCC–BMDCC), and one in the low-DCC portfolio (SLDCC–BLDCC). While the strategies SHDCC–BHDCC and SMDCC–BMDCC outperform the market (the alphas are positive and significant at 10% and 5% levels, respectively), their excess monthly returns are insignificant (indifferent from zero). In contrast, the excess monthly return of the portfolio SLDCC–BLDCC is positive (approximately 1.4%). This return is predicted by the market because the alpha is insignificant and indifferent from zero. Therefore, for arbitrage strategies that buy small-size and sell big-size stocks, the strategy that buys stocks in the SLDCC portfolio and sells stock in the BLDCC portfolio (SLDCC–BLDCC) earns a higher return than the others. This return is predicted by the market.

For arbitrage strategies based on the DCC beta, Table 7.15 shows six strategies that buy higher-DCC beta and sell lower-DCC beta stocks: three strategies in the small-size portfolio (SHDCC–SLDCC, SHDCC–SMDCC, SMDCC–SLDCC) and three strategies in the big-size portfolio

(BHDCC–BLDCC, BHDCC–BMDCC, BMDCC–BLDCC). Both returns and alphas of SHDCC–SMDCC, BHDCC–BLDCC, and BHDCC–BMDCC portfolios are insignificant (indifferent from zero). In contrast, the SHDCC–SLDCC and SMDCC–SLDCC portfolios underperform the market. The alphas of these portfolios are negative and significant at 5 per cent and 10 per cent levels, respectively. However, the excess monthly returns of these portfolios are significant. Only the return of the BMDCC–BLDCC portfolio is positive (approximately 1.11%) and significant at a 5 per cent level. This return is predicted by the market because the alpha is insignificant and indifferent from zero. Therefore, for arbitrage strategies that buy higher-DCC beta and sell lower-DCC beta stocks, the strategy that buys stocks in the BMDCC portfolio and sells stock in the BLDCC portfolio (BMDCC–BLDCC) earns a higher return than the others. This return is predicted by the market. The return of the BMDCC–BLDCC portfolio is lower than that of the SLDCC–-BLDCC portfolio. However, the returns of these arbitrage strategies are smaller than that of the long strategy (SLDCC). Therefore, investors should buy stocks in the SLDCC portfolio to maximise the excess monthly return (approximately 1.42%).

7.4. Summary of Findings

For arbitrage strategies, returns of SHVaR–BHVaR, SM–SL, SU–SD, SHVaR–SMVaR, and BMDCC–BLDCC portfolios are positive and significant. These strategies also outperform the market because their alpha is positive and significant. This implies that returns of smaller-size stocks are higher than that of bigger-size stocks, returns of higher-value stocks are higher than that of lower-value stocks, returns of higher-momentum stocks are higher than that of lower-momentum stocks, returns of high-VaR stocks are higher than that of lower-VaR stocks, and returns of higher-DCC beta stocks are higher than that of lower-DCC beta stocks, respectively. Therefore, this supports the negative correlation between firm size and stock returns (Alhashel, 2021; Fama & French, 1992; Hou & Dijk, 2019; Vu et al., 2019). Also, this supports the positive correlation between firm value and stock returns (Alhashel, 2021; Fama & French, 1992; Tsuji, 2020), between momentum and stock returns (Fama & French, 2012; Singh & Walia, 2021; Wang et al., 2021), and between VaR and stock returns (Aziz & Ansari, 2017; Chen, Chen, & Wu, 2014; Iqbal & Azher, 2014). However, the negative and significant return of SMCVaR–SHCVaR portfolio rejects the negative correlation between CVaR and stock returns recommended by Ling and Cao (2020), Tokpavi & Vaucher (2012), and Vo et al. (2019). All returns of buying higher-illiquidity stocks and selling lower-illiquidity stocks are insignificant. This rejects the positive correlation between illiquidity and stock returns recommended by Amihud et al. (2015), Chen et al. (2019), Gunathilaka et al. (2017). Although all returns of buying higher-CAPM beta stocks and selling lower-CAPM beta stocks are insignificant, the return of buying higher-DCC beta and selling lower-DCC beta stocks (BMDCC–BLDCC) is positive and significant. This supports that while the dynamic beta (DCC beta) can explain stock returns, the static beta (CAPM beta) cannot explain it (Adrian & Franzoni, 2009; Bali, Engle, & Tang, 2017; Engle, 2002). The return of the BMDCC–BLDCC is predicted by the model because the alpha is insignificant. Details of returns and alphas of these arbitrage strategies are shown in Table 7.16.

Table 7.16: Summary of Appropriate Arbitrage Strategies

Arbitrage Strategies	Portfolios	Average Monthly Returns (%)	Average Monthly Alphas (%)
Buy smaller-size stocks – Sell bigger size stocks	SHVaR–BHVaR	2.355***	1.876***
Buy higher-value stocks – Sell lower-value stocks	SM–SL	1.170*	1.079*
Buy higher-momentum stocks – Sell lower-momentum stocks	SU–SD	1.149*	1.436**
Buy higher-VaR stocks – Sell lower-VaR stocks	SHVaR–SMVaR	1.765***	1.482***
Buy lower-CVaR stocks – Sell higher-CVaR stocks	SMCVaR–SHCVaR	−1.024**	−0.727*

Arbitrage Strategies	Portfolios	Average Monthly Returns (%)	Average Monthly Alphas (%)
Buy higher-illiquidity stocks – Sell lower-illiquidity stocks	-	-	-
Buy higher-CAPM beta stocks – Sell lower-CAPM beta stocks	-	-	-
Buy higher-DCC beta stocks – Sell lower-DCC beta stocks	BMDCC–BLDCC	1.112**	−0.257

Notes: the standard errors are robust using Newey & West (1987)

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

At the moment, short sales are not allowed in the HSX; however, investors can find positive returns with long strategies. Details of returns and alphas of appropriate long strategies are shown in Table 7.17. Buying stocks in the SHVaR portfolio generates the highest return (approximately 2.38 percent monthly) for long strategies.

Table 7.17: Summary of Appropriate Long Strategies

Long Strategies	Portfolios	Average Monthly Returns (%)	Average Monthly Alphas (%)
Firm size	SHVaR	2.382**	1.716***
Firm value	H	2.109***	1.910***
Momentum	SU	1.941***	1.599***
VaR	SHVaR	2.382**	1.716***
CVaR	SHCVaR	2.067**	1.413***
Illiquidity	SHIlliq	1.539***	1.038***
CAPM beta	SLCAPM	1.611***	1.138***
DCC beta	MDCC	1.763***	1.865***

Notes: the standard errors are robust using Newey & West (1987)

****Significant at the 1% level. **Significant at the 5% level. *Significant at the 10% level.*

7.5. Conclusion

This chapter studies different stock selections are studied, based on firm size, firm value, momentum, VaR, illiquidity, CAPM beta, and DCC beta. Using both single sorting and double sorting on these firm characteristics, the research found that both long and arbitrage strategies generate positive alpha and return significantly. Therefore, investors can use this information to earn higher returns. For arbitrage strategies, the strategy that buys stocks in the SHVaR portfolio and sells stocks in the BHVaR portfolio (SHVaR–BHVaR) earns the highest monthly return, approximately 2.36 per cent. For long strategies, the strategy that buys high-VaR stocks in the small-size group (SHVaR) earns the highest excess monthly return, approximately 2.38 per cent. Both strategies outperform the market because both monthly alphas are positive, approximately 1.88 per cent for the SHVaR–BHVaR portfolio and 1.73 per cent for the SHVaR portfolio (Table 7.11). However, short sales are not allowed in Vietnam at the moment; therefore, investors can only buy stocks in the SHVaR portfolio.

Chapter 8: Conclusion, Summary of Findings, Recommendations, and Limitations

8.1. Introduction

The main purpose of this thesis is to determine what stock selections bring positive returns for investors on the HSX. To achieve this goal, first, the thesis tests the correlation between stock returns and different firm characteristics such as CAPM beta, DCC beta, size, value, momentum, illiquidity, Value-at-Risk (VaR), conditional Value-at-Risk (CVaR), and illiquidity. Second, this thesis builds an appropriate multifactor model for the HSX. In literature, three-factor, four-factor, and five-factor models are popularly used without reassessing the appropriateness for new markets. This thesis assesses nine factors (market, size, value, Value-at-Risk, conditional Value-at-Risk, illiquidity, investment, and profitability factors) to understand what appropriate combinations of these factors are. Then the GRS test is applied to confirm the most appropriate model for the HSX. Third, stocks are sorted in different portfolios using both single sort and double sort variables, and returns of both long and arbitrage strategies are measured to discover what stock selections bring profit for investors in this market. The sections below summarise the main findings of this thesis and provide some policy recommendations and implications for investors on the HSX.

8.2. Findings

8.2.1. CAPM Beta and DCC Beta

In the CAPM model, only the CAPM beta explains stock returns. Furthermore, CAPM beta is positively correlated with stock returns (Sharpe, 1964). However, in Chapter 5, all regressions reject this hypothesis because all CAPM beta coefficients are insignificant (Panel A, Table 5.18). Therefore, buying higher-CAPM beta stocks and selling lower-CAPM beta stocks should not earn positive returns. Chapter 7 also found that all returns of these strategies are indifferent from zero (Tables 7.7 and 7.14). This rejects the hypothesis in the CAPM model that stocks with higher CAPM beta are considered as higher risk and should have higher returns.

CAPM beta is static, and it cannot explain stock returns. However, a dynamic beta called DCC beta can explain stock returns. DCC beta is positively correlated with stock returns (Bali et al., 2017; Engle, 2002). In Chapter 5, only the FE (double effects) regression supports this hypothesis at a 1 per cent level. Therefore, buying higher-DCC beta stocks and selling lower-DCC beta stocks should earn positive returns. Both BE and FM regressions reject this relationship (Panel B, Table 5.18). Chapter 7 also found that buying medium-DCC beta stocks and selling low-DCC beta stocks in the big size group (BMDCC–BLDCC) earns a significantly positive return (Table 7.15). This is in line with the FE (double effects) regression. However, this challenges the BE and FM estimations that reject the positive correlation between DCC beta and stock returns. Hence, DCC beta may be a better proxy for systematic risk than CAPM beta in explaining stock returns.

8.2.2. Firm Size

Firm size is negatively correlated with stock returns (Alhashel, 2021; Fama & French, 1992; Hou & Dijk, 2019; Vu et al., 2019). In Chapter 5, only the FE (double effects) regression supports this hypothesis at a 1 per cent level. Therefore, buying smaller-size stocks and selling bigger-size stocks should earn positive returns. Both BE and FM regressions reject this relationship (Panels A and B, Table 5.18). Chapter 7 found that buying smaller-size stocks and selling bigger-size stocks earn significantly positive returns in many cases such as buying small-size stocks and selling medium-size stocks (S–M) (Table 7.1), buying small-size stocks and selling big-size stocks in the medium-value group (SM–BM) (Table 7.9), in the up-momentum group (SU–BU) (Table 7.10), in the high-VaR group (SHVaR–BHVaR) (Table

7.11), in the high-CVaR group (SHCVaR–BHCVaR) (Table 7.12), and both the high-illiquid group (SHIlliq–BHIlliq) and medium-illiquid-group (SMIlliq–BMIlliq) (Table 7.13). This is in line with the FE (double effects) regression. However, the high returns of these strategies challenge the BE and FM estimations that reject the negative correlation between firm size and stock returns.

8.2.3. Firm Value

Firm value is positively correlated with stock returns (Alhashel, 2021; Blackburn & Cakici, 2019; Fama & French, 1992; Hanauer & Lauterbach, 2019; Tsuji, 2020). In Chapter 5, all regressions reject this hypothesis because all firm value coefficients are insignificant (Panels A and B, Table 5.18). Therefore, buying higher-value stocks and selling lower-value stocks should not earn positive returns. However, Chapter 7 found that buying medium-value stocks and selling low-value stocks in the small size group (SM–SL) (Table 7.9) earn a significantly positive return. This challenges all regressions that reject the positive correlation between firm value and stock returns.

8.2.4. Momentum

Momentum is positively correlated with stock returns (Blackburn & Cakici, 2019; Fama & French, 2012; Hanauer & Lauterbach, 2019; Singh & Walia, 2021; Wang et al., 2021). In Chapter 5, all regressions support this hypothesis because all momentum coefficients are significant at a 1 per cent level (Panels A and B, Table 5.18). Therefore, buying higher-momentum stocks and selling lower-momentum stocks should earn positive returns. Chapter 7 also found that buying neutral-momentum stocks and selling down-momentum stocks (N–D) (Table 7.3), buying up-momentum stocks and selling down-momentum stocks in the small-size group (SU–SD) (Table 7.10), buying neutral-momentum stocks and selling down-momentum stocks in the big-size group (BN–BD) (Table 7.10) earn significantly positive returns. This is in line with all regressions.

8.2.5. VaR and CVaR

VaR is positively correlated with stock returns (Aziz & Ansari, 2017; Bali & Cakici, 2004; Bali et al., 2007; Chen et al., 2014; Iqbal & Azher, 2014). In Chapter 5, all regressions reject this hypothesis (Panels A and B, Table 5.18). Therefore, buying higher-VaR stocks and selling lower-VaR stocks should not earn positive returns. However, Chapter 7 found that this strategy significantly brings positive returns for investors in the small-size group (SHVaR–SLVaR and SHVaR–SMVaR) (Table 7.11). This challenges all regressions that reject the positive correlation between VaR and stock returns.

In contrast, CVaR is negatively correlated with stock returns (Ling & Cao, 2020; Tokpavi & Vaucher, 2012; Vo et al., 2019). In Chapter 5, all regressions reject this hypothesis because the CVaR coefficients are insignificant (Panels A and B, Table 5.18). Therefore, buying lower-CVaR stocks and selling higher-CVaR stocks should not earn positive returns. Chapter 7 also found that this strategy does not bring positive returns for investors. In particular, the strategy that buys medium-CVaR stocks and sells high-CVaR stocks in the small-size group (SMCVaR-SHCVaR) suffers a monthly loss (Table 7.12). This loss challenges the hypothesis that returns are negatively correlated with CVaR.

8.2.6. Illiquidity

Illiquidity is positively correlated with stock returns (Amihud, 2002; Amihud et al., 2015; Chen et al., 2019; Gunathilaka et al., 2017). In Chapter 5, all regressions reject this hypothesis because all the illiquidity coefficients are insignificant (Panels A and B, Table 5.18). Therefore, buying higher-illiquidity stocks and selling lower-illiquidity stocks should not earn positive returns. Chapter 7 also found that the returns of these strategies are indifferent from zero (Tables 7.6 and 7.13). This is in line with all regressions.

8.2.7. Risk Factors on the HSX

Chapter 6 found that not all nine risk factors (MKT, SMB, HML, UMD, HVaRL, LCVaRH, HILLIQL, RMW, and CMA) explain stock returns on the HSX. Regressions of the returns of market portfolio (MKT) on other risk factors show that different factor models can represent risk models for the HSX: the three-factor model (3FM) created by MKT, SMB, and HML (Fama & French, 1993) or MKT, SMB, and CMA, or MKT, SMB, and HILLIQL; the four-factor model (4FM) created by MKT, SMB, HML, and UMD (Carhart, 1997). The performance of these models is tested using the GRS test (Gibbons et al., 1989) with different portfolios.

Overall, the GRS test shows that the 3FM model (containing the MKT, SMB, and CMA factors) has a better performance than other multifactor models. The GRS test of this model is statistically significant in many portfolios: Size–Value portfolio (5%), Size–CVaR portfolio (2%), Size–Illiquidity (3%), Size–CAPM beta (5%), and Size–DCC beta (1%). Therefore, the 3FM containing the MKT, SMB, and CMA is used as a benchmark to evaluate the performance of different strategies. The summary of GRS tests is provided in Table 6.10 in Chapter 6.

8.3. Recommendations and Implications

First, researchers often use Fama–MacBeth regression approach for testing asset pricing models (Fama, 2014; Harvey et al., 2016). However, this method is biased if the residuals exist the individual effects or both individual and time effects (Petersen, 2009). The latest development of panel regressions with clustering techniques improves the standard errors for possible effects that existed in the residuals (Millo, 2019; Petersen, 2009; Sun et al., 2018;

Thompson, 2011). Therefore, the results of the panel regressions should test the existence of the individual effects, time effects, or both effects and use the clustering techniques to enhance the standard errors of estimated coefficients. However, half of the published papers using panel regressions did not adjust the standard errors (Petersen, 2009). This thesis reports the robustness of estimated coefficients using double clustering techniques because both individual and time effects exist in the residual. The strategies based on robustness panel regression using double clustering in this thesis are more consistent than those based on the BE and FM regressions.

Second, many papers use the three-factor model developed by Fama and French (1993), the four-factor model developed by Carhart (1997), and the five-factor model developed by Fama and French (2015) as empirical asset pricing models without testing the appropriateness of these factors in new markets. Because these models are tested in the US, they may not be appropriate for other markets (especially emerging markets), because of the differences in economic structures between developed and developing markets (Hanauer & Lauterbach, 2019; Ragab et al., 2020). In addition, the effects of publicised factors may be reduced in explaining stock returns over time because investors can learn, and trade based on the mispricing of those factors. Therefore, the effects of those factors disappear or decay after the publications (Jacobs & Müller, 2020; Mclean & Pontiff, 2016). This thesis studies nine risk factors with a new conditional Value-at-Risk factor (LCVaRH) and finds that the performances of traditional models developed by Carhart (1997), Fama and French (1993; 2015) are worse than the combination of the market portfolio (MKT), the size factor (SMB), and the investment factor (RMW). Currently, only the market portfolio exists on the HSX. Other factors are not constructed. Therefore, the HSX should consider constructing other factors because the multifactor models constructed by these factors can be used to evaluate portfolio performance in trading and to evaluate market efficiency (Fama, 2014). The findings of strategies that bring highly positive returns and outperform the market imply that the HSX is not efficient. This opens the door for future research by adjusting the publicised risk factors or creating new ones.

Third, there is limited research on stock selection in Vietnam because of the immature market and limited data availability compared to developed markets. Data analysts and researchers cannot approach databases (Eikon and Bloomberg) and journals because of high costs. Even universities in Vietnam cannot afford to subscribe to these resources for their students and lecturers. In addition, investors are not familiar with research papers. When they need advice for buying and selling stocks, they ask brokers who do not test the strategies they advised. Brokers give their advice based on simple statistics on historical prices or their biased opinions. Therefore, more publications on stock selections will help brokers and investors in consulting and trading.

Last, the framework in this thesis not only works in emerging markets, but also works in developed ones. In addition, new factors may be added to explain stock returns in the future. They are easy to add to the framework to examine the efficiency and effectiveness in explaining stock returns using any data in both emerging and developed markets. Although the new conditional Value-at-Risk factor (LCVaRH) constructed in this thesis is not significant in the HSX, this factor should be tested in other markets for further verification.

Overall, results from this thesis recommend that scholars should examine the existence of different effects individual and/or time effects of data to select the appropriate regression for their research. Also, publicised factors should be tested before being used because of differences in economic structures and some known factors reduce (or disappear) their effects in some markets. Better, scholars should build new factors to explain stock returns. Moreover, universities (especially in developing markets like Vietnam) should invest the databases of journals and data for their lecturers, researchers, and students to improve the quality of the research and training in economics, finance, and stock markets. This will provide quality researchers and analysts for the market. Additionally, data providers (companies) should cooperate with universities to exploit and convert raw data into useful information such as risk factors and trading strategies to give insight and concrete evidence for investors and policymakers.

8.4. Limitations and Future Research

Although this thesis is comprehensive in studying different characteristics affecting stock returns both using individual stocks and portfolios for the HSX, there are some limitations. First, Harvey and Liu (2019) found that more than 300 factors affect stock returns; however, this thesis does not cover all variables because of the limitation of time, data, and knowledge. Second, this thesis does not cover the effects of the global financial crisis and the pandemic COVID-19 periods. Third, variables in this thesis are collected from trading and financial statements. Therefore, macroeconomics and microeconomics are left for further study. Furthermore, all factors in this thesis cannot explain the risks of the Size–Momentum, and Size–VaR portfolios. Therefore, other factors should be considered to explain the risks of these portfolios. Last, this thesis and previous studies use breakpoints and percentiles to construct portfolios and risk factors. However, with the developments of machine learning and deep learning, scholars should utilise these innovative techniques to find new patterns in the data where they may find new discoveries in this field.

8.5. Conclusion

First, this thesis found that based on understanding what factors affect stock returns, investors can form appropriate strategies to pick stocks for their trading. The FE regression with individual and time effects (double effects) shows they are a better method of explaining stock returns because this regression can measure these effects and all coefficients can be robust by double clustering to reduce the biases. The traditional methods using BE and FM regressions cannot deal with these issues. Furthermore, the stock selection strategies based on the coefficients of the FE (double effects) regression are more appropriate than those of the BE and FM regressions. In particular, the significance of firm size, momentum, and DCC beta in the FE (double effects) regression significantly brings positive returns for corresponding arbitrage strategies. Second, this thesis found that the combination of the MKT, SMB, and CMA factors explains the risks better for the HSX. However, this thesis finds that returns of long and arbitrage strategies are high and outperform the market. This is a signal that this market is not efficient. To make the market more efficient, this thesis recommends that policymakers revise the available factors in the literate or create new ones to better explain stock returns. Furthermore, more papers on stock selection strategies should be published to help investors have a tool to make better decisions in investment. Last, the framework in this thesis can be used for both developed and developing markets.

Appendix

Table 1: Sample Stocks and Their Industry

No.	Stocks	Industries
1	VNM	Dairy Product Manufacturing
2	HPG	Steel Product Manufacturing from Purchased Steel
3	FPT	Software Publishers
4	DHG	Pharmaceutical and Medicine Manufacturing
5	REE	Building Equipment Contractors
6	SBT	Sugar and Confectionery Product Manufacturing
7	PPC	Electric Power Generation
8	LGC	Highway, Street, and Bridge Construction
9	VHC	Seafood Product Preparation and Packaging
10	GMD	Support Activities for Water Transportation
11	PVD	Drilling Oil and Gas Wells
12	HT1	Cement and Concrete Product Manufacturing
13	CII	Highway, Street, and Bridge Construction
14	DPM	Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing
15	PAN	Other Food Manufacturing
16	PVT	Deep Sea, Coastal, and Great Lakes Water Transportation
17	VSH	Electric Power Generation
18	KDC	Bakeries and Tortilla Manufacturing
19	BMP	Plastics Product Manufacturing
20	HAG	Fruit and Tree Nut Farming
21	HSG	Steel Product Manufacturing from Purchased Steel
22	ANV	Seafood Product Preparation and Packaging
23	DRC	Rubber Product Manufacturing
24	TRA	Pharmaceutical and Medicine Manufacturing
25	DMC	Pharmaceutical and Medicine Manufacturing
26	HBC	Residential Building Construction
27	IMP	Pharmaceutical and Medicine Manufacturing
28	DBC	Animal Slaughtering and Processing
29	SAM	Other Electrical Equipment and Component Manufacturing
30	VIS	Steel Product Manufacturing from Purchased Steel
31	DCL	Pharmaceutical and Medicine Manufacturing
32	NSC	Other Crop Farming
33	DPR	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
34	TBC	Electric Power Generation
35	VSC	Support Activities for Water Transportation
36	TMS	Freight Transportation Arrangement
37	FMC	Seafood Product Preparation and Packaging
38	OPC	Pharmaceutical and Medicine Manufacturing
39	SJD	Electric Power Generation

No.	Stocks	Industries
40	PAC	Other Electrical Equipment and Component Manufacturing
41	HRC	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
42	TCM	Cut and Sew Apparel Manufacturing
43	TRC	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
44	PGC	Natural Gas Distribution
45	BBC	Sugar and Confectionery Product Manufacturing
46	CLC	Tobacco Manufacturing
47	TAC	Grain and Oilseed Milling
48	SVI	Converted Paper Product Manufacturing
49	LCG	Highway, Street, and Bridge Construction
50	TTF	Household and Institutional Furniture and Kitchen Cabinet Manufacturing
51	RAL	Electric Lighting Equipment Manufacturing
52	SSC	Other Crop Farming
53	VNS	Taxi and Limousine Service
54	TNA	Metal and Mineral (except Petroleum) Merchant Wholesalers
55	COM	Gasoline Stations with Convenience Stores
56	SMC	Metal and Mineral (except Petroleum) Merchant Wholesalers
57	PET	Electrical and Electronic Goods Merchant Wholesalers
58	HAX	Automobile Dealers
59	VTO	Deep Sea, Coastal, and Great Lakes Water Transportation
60	ACL	Seafood Product Preparation and Packaging
61	HAI	Chemical and Allied Products Merchant Wholesalers
62	GMC	Cut and Sew Apparel Manufacturing
63	ST8	Motor Vehicle and Motor Vehicle Parts and Supplies Merchant Wholesalers
64	DHA	Nonmetallic Mineral Mining and Quarrying
65	TSC	Chemical and Allied Products Merchant Wholesalers
66	DQC	Electric Lighting Equipment Manufacturing
67	TYA	Other Electrical Equipment and Component Manufacturing
68	ABT	Seafood Product Preparation and Packaging
69	GIL	Apparel Accessories and Other Apparel Manufacturing
70	KHP	Electric Power Transmission, Control, and Distribution
71	SC5	Residential Building Construction
72	SGT	Professional and Commercial Equipment and Supplies Merchant Wholesalers
73	RIC	Gambling Industries
74	SFI	Support Activities for Water Transportation
75	TNC	Resin, Synthetic Rubber, and Artificial Synthetic Fibers and Filaments Manufacturing
76	VIP	Inland Water Transportation
77	LSS	Sugar and Confectionery Product Manufacturing
78	LBM	Clay Product and Refractory Manufacturing
79	UIC	Electric Power Transmission, Control, and Distribution
80	VNE	Utility System Construction
81	ASP	Natural Gas Distribution
82	CDC	Civil and Industrial Construction, Manufacturing, Processing Metal Components

No.	Stocks	Industries
83	SFC	Gasoline Stations with Convenience Stores
84	HMC	Metal and Mineral (except Petroleum) Merchant Wholesalers
85	SCD	Beverage Manufacturing
86	TPC	Plastics Product Manufacturing
87	MCP	Other Fabricated Metal Product Manufacturing
88	HAP	Converted Paper Product Manufacturing
89	VTB	Communications Equipment Manufacturing
90	HTV	Inland Water Transportation
91	PJT	Deep Sea, Coastal, and Great Lakes Water Transportation
92	BMC	Metal Ore Mining
93	KMR	Textile Furnishings Mills
94	PNC	Office Supplies, Stationery, and Gift Stores
95	LAF	Other Food Manufacturing
96	L10	Foundation, Structure, and Building Exterior Contractors
97	MHC	Inland Water Transportation
98	SAV	Household and Institutional Furniture and Kitchen Cabinet Manufacturing
99	GTA	Other Wood Product Manufacturing
100	NAV	Building Material and Supplies Dealers

Note: Data is collected from Eikon database and Vietstock website, accessed 8 March 2021

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