NNT/NL : 0000AIXM0000/000ED372

THÈSE DE DOCTORAT

Soutenue à Aix-Marseille Université
le JJ mois AAAA par

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THE GROWTH, MOMENTUM, AND SIZE EFFECTS IN THE VIETNAMESE STOCK MARKET

Discipline

Sciences de Gestion

École doctorale

ED 372 – SCIENCES ECONOMIQUES ET DE GESTION

Laboratoire/Partenaires de recherche
renseigner les partenaires institutionnels
et les partenaires privés
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Liste de publications et participation aux conférences

1) Liste des publications réalisées dans le cadre du projet de thèse :

    1. Quy Duong, L., & Bertrand, P. (2021). The size effect and default risk: Evidence from the Vietnamese stock market. *Review of Financial Economics*, 00, 1–12. https://doi.org/10.1002/rfe.1149
    2. Quy Duong, L., & Bertrand, P. (2021). Momentum explains the growth effect: The case of Vietnamese stock market. Accepted with Minor Revision in *International Journal of Finance and Economics.*
    3. Quy Duong, L., & Bertrand, P. (2022). Overreaction and momentum in the Vietnamese stock market. Accepted with Major Revision in *Managerial Finance.*

2) Participation aux conférences et écoles d'été au cours de la période de thèse :
    1. The 2020 UEH International Conference on Business and Finance, the University of Economics Ho Chi Minh City, Vietnam, August 28th, 2020
    2. 3rd International Conference on contemporary issues in economics, management and business, National Economic University, Vietnam, November 11th, 2020
    3. 37th International Conference of the French Finance Association, French Finance Association, French, May 28th, 2021.

Résumé

Since being presented in the 1960s, the Efficient Market Hypothesis (EMH) has become a main paradigm in the financial industry. A great number of financial theories are based on the assumption of market efficiency. Although there is supportive evidence in the US during 1960s and 1970s, several empirical results that seem to be inconsistent with the market efficiency are found. They are known as financial market anomalies. Three important anomalies attracting significant attention amongst investment theory academics and stock market practitioners are the value/growth, momentum, and size effects.

The value/growth effect is the difference of average returns between the value and growth stocks. Value (growth) stocks are defined as stocks with low (high) valuations relative to their assets or earnings. While the value premium exists in developed markets namely the US, Europe, Japan, etc. (McWilliams, 1966; Basu, 1977; Fama and French, 1993, 1998, 2007a, 2017; Jaffe et al., 2020); growth stocks outperform value stocks in several emerging markets such as India, Argentina, India, Thailand, and Russia (Ebrahim et al., 2014; Leite et al., 2018).

The momentum effect is the tendency for shares with high past returns during a intermediate period (from three to twelve months) to earn a high return in the next three to twelve months. At the same time, stocks with low past returns would continue falling. Evidence of momentum is discovered in various equity markets in America, Europe and Asia (Jegadeesh and Titman, 1993, 2001; Asness, 1997; Van Dijk and Huibers, 2002; Doukas and McKnight, 2005; Antonio et al., 2007; Cakici et al., 2013; Byun et al., 2016; Bhattacharya et al., 2017; Huhn and Scholz, 2019; Butt et al., 2021).

A variety of papers report that stocks with low market capitalization generate abnormal positive returns, which is considered as the size effect. In the US, small stocks outperform big stocks from 1936 to 1985 (Banz, 1981; Reinganum, 1981; Keim, 1983; Lamoureux and Sanger, 1989). Although the size premium seems to

disappear in the US and several developed European markets after the early 1980s, a strong size effect still exists in many developed as well as emerging markets over 1963-2014 (Hou and Van Dijk, 2019).

Despite of the fairly extensive literature of these anomalies in numerous equity markets, studies investigating the Vietnamese stock market are few and far between. Therefore, the thesis aims to contribute to the extant literature by intensively examining the value/growth, momentum, and size effects in Vietnam, an important frontier emerging market. Thanks to a rapid growth during the last decade, Vietnam ranks in the top 40 worldwide in terms of the market capitalization. With one-third of total capitalization belonging to foreign investors, the empirical findings are applicable to not only Vietnamese investors but also international individual and institutional investors.

The first result is that investing in the growth portfolio leads to the highest average return in Vietnam, at more than 12.4% per year during 2009-2019. In seven out of ten sample years, growth stocks outperform value stocks. There is solid proof of a growth effect in Vietnam, contrary to the value effect in developed markets. The CAPM and Fama-French multifactor models cannot give a plausible explanation to the growth effect in the Vietnamese stock market. Furthermore, three out of four mimic factors (the value, investment, and profitability factors) have insignificant intercepts in the redundancy test of Barillas and Shanken (2017). Consequently, these factors include no incremental information on expected returns relative to the market and size factors.

Meanwhile, thanks to significant intercepts in the redundancy test, the momentum factor contains information incremental to the CAPM and Fama-French models. A model including the market, size, and momentum factors completely explains Vietnam's growth effect. Due to high exposure to the momentum factor, momentum is the main reason for excess returns on growth stocks. Addtionally, the return of momentum factor is positive in only nine months after portfolio formation. From the tenth month, the momentum factor delivers significantly negative return, which corroborates that momentum arises from the delayed overreaction of investors. Most growth stocks are issued by big and highly profitable firms, which represent attractive investments. Hence, due to the presence of herd behavior, Vietnamese investors are inclined to overreact to good news about their past stock returns, driving their share prices further from long-term values. It is the key reason why the growth portfolio outperforms other portfolios in Vietnam.

Secondly, a trading strategy based on overreaction of investors generates abnormal positive returns. Motivated by models of Daniel et al. (1998) and Byun et al. (2016), we propose a measure of overreaction in Vietnam based on the trading volume and the sign of stock returns. A combination of high trading volume and positive (negative) returns implies overreaction to positive (negative) private information, which pushes stock prices above (below) their intrinsic values. Stocks that have experienced a stronger upward overreaction earn the higher average returns. A strategy, which is long shares with upward overreaction and short shares with downward overreaction, earns a considerably positive profit of 10.2% per year in Vietnam over 2009-2019. The return of this trading strategy is still significant even after adjusting for the momentum effect. However, the momentum profit disappears after controlling for the effect of overreaction. Furthermore, by double-sorting stocks on their past returns and levels of overreaction, we find that holding past returns constant, the average returns of portfolios increase monotonically with their measure of overreaction. By contrast, controlling for overreaction, past returns have no predictability for the cross-section of returns. Given this backdrop, momentum in Vietnam arises from the investors' overreaction to private information as suggested by Daniel et al. (1998).

Finally, the size effect is reported in Vietnam from 2009 to 2019. Small-cap stocks generate the highest average return than remaining stocks, at approximately 19,3% per year. The evidence of size premium is robust even after excluding the bubble period. Then, we examine whether the size is a proxy for the distress-risk factor in Vietnamese stock returns. The debt-to-equity ratio and distance-to-default of Merton (1974) are used as risk proxies. By triple-sorting stocks on their market capitalization and risk proxies, we document that excess returns on small shares are concentrated in stocks with high distress risk. When bankruptcy risk is measured by the distance-to-default, the average return on small high-risk shares is more than

35% per annum, close to four times the average return on small low-risk shares. Additionally, the explanatory power of size factor is evaluated when the default-risk neutrality is imposed. Adopting the technique suggested by Groot and Huij (2018), stocks are initially ranked on their risk proxies before being divided into small and big portfolios to construct neutral size factors. As a result, these small and big portfolios have virtually equal distress-risk proxies. Hence, neutral size factors are less exposed to bankruptcy risk than the ordinary factor of Fama and French (2016). Empirical results show that the explanatory power of size factor decreases when the default-risk neutrality is imposed. When the distance-to-deafult is risk proxy, the neutral size factor is likely to be an insignificant factor. Taken together, the size premium in Vietnam seems to arise from distress risk, which is consistent with the risk-based explanation.

In conclusion, although the findings look similar to those from literature at the first sight, we also discover a contradictory result. On the one hand, there is evidence of a growth effect in Vietnam, which implies that a strong return pattern found in developed stock markets might be inaccurate in emerging markets. Growth stocks outperform value stocks since Vietnamese investors tend to overreact to the good news about the past returns of growth shares. On the other hand, the momentum and size effects in Vietnam follow the same trends documented in other stock markets. While momentum arises from investors' overreaction to private information, default risk is the main source of size premim. Investors and investment managers could use empirical findings from this thesis to value shares and form up investment portfolios for the Vietnamese market.

Keywords : anomalies, value/growth, size premium, momentum, overreaction, default risk

Résumé

Depuis sa présentation dans les années 1960, l'hypothèse de l'efficience des marchés (HEM) est devenue un paradigme majeur dans le secteur financier. Un grand nombre de théories financières sont basées sur l'hypothèse de l'efficience des marchés. Bien qu'il existe des preuves de soutien aux États-Unis dans les années 1960 et 1970, plusieurs résultats empiriques qui semblent être incompatibles avec l'efficience des marchés ont été trouvés. Ils sont connus sous le nom d'anomalies des marchés financiers. Trois anomalies importantes attirent l'attention des théoriciens de l'investissement et des praticiens des marchés boursiers : les effets valeur/croissance, momentum et taille.

L'effet valeur/croissance est la différence de rendement moyen entre les actions de valeur et de croissance. Les actions de valeur (croissance) sont définies comme des actions dont la valorisation est faible (élevée) par rapport à leurs actifs ou à leurs bénéfices. Alors que la prime de valeur existe sur les marchés développés, à savoir les États-Unis, l'Europe, le Japon, etc. (McWilliams, 1966 ; Basu, 1977 ; Fama et French, 1993, 1998, 2007, 2017 ; Jaffe et al., 2020), les actions de croissance surpassent les actions de valeur sur plusieurs marchés émergents tels que l'Inde, l'Argentine, l'Inde, la Thaïlande et la Russie (Ebrahim et al., 2014 ; Leite et al., 2018).

L'effet momentum est la tendance des actions dont les rendements passés sont élevés pendant une période intermédiaire (de trois à douze mois) pour obtenir un rendement élevé au cours des trois à douze mois suivants. Dans le même temps, les actions dont les rendements passés sont faibles continueront à baisser. Des preuves de l'effet momentum sont découvertes sur différents marchés d'actions en Amérique, en Europe et en Asie (Jegadeesh et Titman, 1993, 2001 ; Asness, 1997 ; Van Dijk et Huibers, 2002 ; Doukas et McKnight, 2005 ; Antonio et al., 2007 ; Cakici et al., 2013 ; Byun et al., 2016 ; Bhattacharya et al., 2017 ; Huhn et Scholz, 2019 ; Butt et al., 2021).

De nombreux articles rapportent que les actions à faible capitalisation boursière génèrent des rendements positifs anormaux, ce qui est considéré comme l'effet de taille. Aux États-Unis, les petites actions ont surperformé les grandes entre 1936 et 1985 (Banz, 1981 ; Reinganum, 1981 ; Keim, 1983 ; Lamoureux et Sanger, 1989). Bien que la prime de taille semble avoir disparu aux États-Unis et sur plusieurs marchés européens développés après le début des années 1980, un fort effet de taille existe toujours sur de nombreux marchés développés et émergents entre 1963 et 2014 (Hou et Van Dijk, 2019).

Malgré une littérature assez importante sur ces anomalies dans de nombreux marchés d'actions, les études sur le marché vietnamien sont peu nombreuses. Cette thèse vise donc à contribuer à la littérature existante en examinant de manière approfondie les effets valeur/croissance, momentum et taille au Vietnam, un important marché émergent. Grâce à une croissance rapide au cours de la dernière décennie, le Vietnam se classe dans le top 40 mondial en termes de capitalisation boursière. Avec un tiers de la capitalisation totale appartenant à des investisseurs étrangers, les résultats empiriques sont applicables non seulement aux investisseurs vietnamiens mais aussi aux investisseurs individuels et institutionnels internationaux.

Le premier résultat est que l'investissement dans le portefeuille de croissance conduit au rendement moyen le plus élevé au Vietnam, à plus de 12,4 % par an pendant la période 2009-2019. Pendant sept des dix années de l'échantillon, les actions de croissance ont surpassé les actions de valeur. Il existe des preuves solides d'un effet de croissance au Vietnam, contrairement à l'effet de valeur sur les marchés développés. Le MEDAF et les modèles multifactoriels de Fama-French ne peuvent fournir une explication plausible de l'effet de croissance sur le marché boursier vietnamien. En outre, trois des quatre facteurs mimétiques (les facteurs de valeur, d'investissement et de rentabilité) ont des intercepts non significatifs dans le test de redondance de Barillas et Shanken (2017). Par conséquent, ces facteurs ne comprennent aucune information supplémentaire sur les rendements attendus par rapport aux facteurs de marché et de taille.

Parallèlement, grâce à des intercepts significatifs dans le test de redondance, le facteur momentum contient des informations supplémentaires par rapport aux modèles CAPM et Fama-French. Un modèle incluant les facteurs marché, taille et momentum explique complètement l'effet de croissance du Vietnam. En raison de la forte exposition au facteur momentum, ce dernier est la principale raison des rendements excédentaires des actions de croissance. De plus, le rendement du facteur momentum n'est positif que neuf mois après la formation du portefeuille. À partir du dixième mois, le rendement du facteur momentum est significativement négatif, ce qui corrobore le fait que le momentum résulte de la surréaction différée des investisseurs. La plupart des actions de croissance sont émises par des entreprises importantes et très rentables, qui représentent des investissements intéressants. Par conséquent, en raison de la présence d'un comportement grégaire, les investisseurs vietnamiens sont enclins à réagir de manière excessive aux bonnes nouvelles concernant les rendements passés de leurs actions, ce qui éloigne le cours de leurs actions des valeurs à long terme. C'est la raison principale pour laquelle le portefeuille de croissance surperforme les autres portefeuilles au Vietnam.

Deuxièmement, une stratégie de trading basée sur la surréaction des investisseurs génère des rendements positifs anormaux. Motivés par les modèles de Daniel et al. (1998) et de Byun et al. (2016), nous proposons une mesure de la surréaction au Vietnam basée sur le volume de transactions et le signe des rendements boursiers. La combinaison d'un volume de transactions élevé et de rendements positifs (négatifs) implique une surréaction à des informations privées positives (négatives), ce qui pousse les prix des actions au-dessus (en dessous) de leurs valeurs intrinsèques. Les actions qui ont connu une plus forte surréaction à la hausse obtiennent les rendements moyens les plus élevés. Une stratégie consistant à acheter des actions avec une surréaction à la hausse et à vendre des actions avec une surréaction à la baisse permet de réaliser un bénéfice considérablement positif de 10,2 % par an au Vietnam sur la période 2009-2019. Le rendement de cette stratégie de trading reste significatif même après ajustement de l'effet momentum. Cependant, le bénéfice du momentum disparaît après avoir contrôlé l'effet de la surréaction. En outre, en triant doublement les actions en fonction de leurs rendements passés et de leurs niveaux de surréaction, nous constatons qu'en maintenant constants les rendements passés, les rendements moyens des portefeuilles augmentent de façon monotone avec leur mesure de surréaction. En revanche, si l'on tient compte de la surréaction, les rendements passés ne sont pas prévisibles pour la section transversale des rendements. Dans ce contexte, le momentum au Vietnam résulte de la surréaction des investisseurs à l'information privée, comme le suggèrent Daniel et al. (1998).

Enfin, l'effet de taille est rapporté au Vietnam de 2009 à 2019. Les actions de petite capitalisation génèrent le rendement moyen le plus élevé par rapport aux autres actions, soit environ 19,3 % par an. La preuve de la prime de taille est robuste même après avoir exclu la période de la bulle. Nous examinons ensuite si la taille est un indicateur du facteur de risque de détresse dans les rendements des actions vietnamiennes. Le ratio dette/fonds propres et la distance par rapport à la défaillance de Merton (1974) sont utilisés comme indicateurs de risque. En triant les actions en fonction de leur capitalisation boursière et de leurs indicateurs de risque, nous montrons que les rendements excessifs des petites actions sont concentrés dans les actions présentant un risque de détresse élevé. Lorsque le risque de faillite est mesuré par la distance au défaut, le rendement moyen des petites actions à haut risque est supérieur à 35 % par an, soit près de quatre fois le rendement moyen des petites actions à faible risque. De plus, le pouvoir explicatif du facteur taille est évalué lorsque la neutralité du risque de défaut est imposée. En adoptant la technique suggérée par Groot et Huij (2018), les actions sont initialement classées en fonction de leurs proxys de risque avant d'être divisées en petits et gros portefeuilles pour construire des facteurs de taille neutres. Par conséquent, ces petits et grands portefeuilles ont des proxys de risque de détresse pratiquement égaux. Par conséquent, les facteurs de taille neutre sont moins exposés au risque de faillite que le facteur ordinaire de Fama et French (2016). Les résultats empiriques montrent que le pouvoir explicatif du facteur de taille diminue lorsque la neutralité du risque de défaillance est imposée. Lorsque la distance au défaut est un proxy de risque, le facteur de taille neutre est susceptible d'être un facteur non significatif. Dans l'ensemble, la prime de taille au Vietnam semble découler du risque de détresse, ce qui est cohérent avec l'explication basée sur le risque.

En conclusion, bien que les résultats semblent à première vue similaires à ceux de la littérature, nous découvrons également un résultat contradictoire. D'une part, il existe des preuves d'un effet de croissance au Vietnam, ce qui implique qu'un modèle de rendement fort trouvé sur les marchés boursiers développés pourrait être inexact sur les marchés émergents. Les actions de croissance surperforment les actions de valeur car les investisseurs vietnamiens ont tendance à réagir de manière excessive aux bonnes nouvelles concernant les rendements passés des actions de croissance. D'autre part, les effets momentum et taille au Vietnam suivent les mêmes tendances que celles documentées sur d'autres marchés boursiers. Alors que le momentum résulte de la réaction excessive des investisseurs à l'information privée, le risque de défaut est la principale source de la prime de taille. Les investisseurs et les gestionnaires d'investissement pourraient utiliser les résultats empiriques de cette thèse pour évaluer les actions et constituer des portefeuilles d'investissement pour le marché vietnamien.

Mots clés : anomalies, valeur/croissance, prime de taille, momentum, surréaction, risque de défaut.

Abstract

Over recent decades, many debates have sparked among professionals and academics with regard to the efficiency of financial markets. Several key aspects that challenge the market efficiency are the value/growth, momentum, and size effects. The various and different findings from many stock markets imply that the value/growth, momentum, and size effects should be appropriately concluded for individual markets. Although a large body of research about these anomalies has been undertaken, the Vietnamese market has been mostly underrepresented in the academic literature. Hence, the main objective of the thesis is to comprehensively investigate the growth, momentum, and size effects in the Vietnamese market, one of the most dynamic markets in Asia. According to the World Bank data, Vietnam ranks in the top 40 worldwide in terms of the market capitalization of domestic listed stocks. The recent decade observes a rapid growth in the Vietnamese market capitalization, at approximately 19,3% per year. The total value of traded stocks rises dramatically, from nearly $8 billion in 2009 to about $56.9 billion in 2020. Vietnam attracts massive attention of foreign investors, who account for one-third of Vietnamese total market capitalization. The thesis contributes to extant studies and practical investment management in the following value-enhancing aspects.

Firstly, while there is empirical evidence of the value effect in various developed stock markets, the growth effect is documented in Vietnam. In seven out of ten years, investing in growth stocks generates higher returns than value stocks. The CAPM and Fama-French multifactor models fail to explain the growth effect in Vietnam. Among four mimic factors, only the size factor has a significant intercept in the redundancy test. However, a model including the market, size, and momentum factors gives an appropriate explanation of growth effect. Because of high exposure to the momentum factor, the growth portfolio's superior return arises from the momentum effect. Furthermore, by tracking the momentum return up to 24 months following portfolio formation, we examine three main hypotheses explaining the

momentum effect. Since the momentum factor provides positive profitability in only nine months after portfolio formation, the delayed overreaction is likely to be the key reason behind Vietnam's momentum effect.

Secondly, a measure of delayed overreaction in Vietnam is build based on trading volume and the sign of stock returns. A combination of high trading volume and positive returns indicates overreaction to positive private information, pushing stock prices above their intrinsic values. Conversely, a high trading volume associated with negative returns implies overreaction to negative private information, which forecasts a decrease in share prices. Ranking stocks on their levels of overreaction, we find that stocks experiencing a stronger upward overreaction earn a higher average return. Additionally, the momentum profit disappears after controlling for the effect of overreaction, whereas the trading strategy based on overreaction provides significant returns even we adjust for the momentum effect. Using double sorts, we document that controlling for past returns, the average returns of portfolios increase monotonically with their measure of overreaction. Therefore, it could be concluded that momentum in Vietnam arises from the investors' overreaction to private information.

Finally, although numerous researchers agree about the existence of size premium, they disagree about the risk-based explanation. The thesis investigates the relationship between size premium and default risk in the Vietnamese stock market. Since small-cap stocks generate the highest average return than remaining stocks, the size effect is reported in Vietnam. The debt-to-equity ratio and distance-to-default of Merton (1974) are used as distress-risk proxies. By ranking stocks on their market capitalization and risk proxies, we find that the superior return of small portfolio is concentrated in high-risk stocks. Moreover, the explanatory power of size factor decreases when the default-risk neutrality is applied. Given this backdrop, the size premium in Vietnam seems to arise from default risk, which corroborates the risk-based explanation.

Remerciements

I am especially grateful to Professor Philippe Bertrand for his academic recommendations and valuable suggestions on my thesis. This paper cannot be completed without his supervision.

I would like to express my acknowledgement and appreciation towards my parents and brother, who always supported me with love and advice! I would like to thank my dear friends, Ta Quang Son and Le Thanh Tung. Without their support, the work of data analysis would not be completed. I also would like to thank my Ph.D. classmate, Vuong Giang, who provides many useful bits of advice regarding the Vietnamese stock market.

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1. Introduction

1.1. Motivation

Market efficiency has been an intriguing subject for financial economists for a very long time. Although many tests in the US stock market corroborate the Efficient Market Hypothesis (EMH) (Jensen, 1978), the precision of EMH is doubtful. According to the EMH, available information is fully reflected in the current asset prices therefore future returns cannot be predicted on the basis of past information. However, several trading strategies based on historical information provide patterns of average returns challenging the market efficiency. They are known as anomalies. The most important market anomalies, which have recently attracted special attention by academics and researchers, are the value/growth, momentum, and size effects.

The value/growth effect is the difference of average returns between the value and growth stocks. Value stocks are low-priced compared to their fundamentals such as book value, profits, cash flow, etc., while growth stocks are expensive compared to their fundamentals. In developed markets namely the US, Europe, and Japan, investing in value shares tends to be more profitable than in growth shares, which is considered as the value effect (McWilliams, 1966; Basu, 1977; Fama and French, 1993, 1998, 2007a, 2017; Jaffe et al., 2020). In contrast, growth stocks earn a higher average return than value stocks in several emerging markets such as India, Argentina, India, Thailand, and Russia (Ebrahim et al., 2014; Leite et al., 2018).

The momentum effect is the positive relation between a stock's return and its previous performance. Shares with high past returns during a medium period (about 3 - 6 months) are grouped into the winner portfolio, while stocks with the lowest average past returns are assigned into the loser portfolio. Subsequently, the winner outperforms the loser in the next intermediate interval (from 3 to 12 months). Evidence of the momentum effect is well-documented in numerous equity markets. In the US, momentum exists in different periods (Jegadeesh and Titman, 1993, 2001; Asness, 1997; Asness et al., 2013; Byun et al., 2016; Bhattacharya et al., 2017). The momentum effect is also uncovered in various developed markets and emerging markets in Europe, Asia, and Latin American (Van Dijk and Huibers, 2002; Doukas and McKnight, 2005; Antonio et al., 2007; Huhn and Scholz, 2019; Cakici et al., 2013; Butt et al., 2021).

The size anomaly refers to the negative relation between the stock return and the market capitalization. Small size equities have a tendency to earn significantly higher returns than big size equities. This phenomenon was initially addressed by Banz (1981), who found the size premium on the New York Stock Exchange between 1936 to 1975. Later on, the size effect in the US stock market is reaffirmed in various periods: 1963-1977 (Reinganum, 1981); 1963-1979 (Keim, 1983); 1973-1985 (Lamoureux and Sanger, 1989). Although the size anomaly in the US seems to be disappear after the early 1980s, Hou and Van Dijk (2019) find a strong size effect in an international sample of 22 developed and 19 emerging markets during 1964-2014, which implies a large size premium in global stock markets in recent decades.

Despite of the fairly extensive literature of these anomalies in both developed and emerging markets, the number of research studies investigating Vietnam market is very limited. The unsettled questions about the value/growth, momentum, and size effects in Vietnam encourage me to carry out more investigations about these effects and the reason behind them. The thesis contributes to the related literature by intensively examining the value/growth, momentum, and size effects in Vietnam, an important frontier emerging market. The key research questions are summarized in section 1.2. Furthermore, Vietnam ranks in the top 40 worldwide in terms of the market capitalization and attracts a huge amount of international investments. Notably, one-third of Vietnamese total market capitalization belongs to foreign investors. Two exchange-traded funds specializing in Vietnam are listed in the London and New York stock exchanges. Hence, the thesis aims to provide a deeper understanding of Vietnamese stock returns for not only Vietnamese investors but also international investors and fund managers, which enables them to better implement trading strategies.

1.2. Research questions

1. Whether the value or the growth effect exist in the Vietname stock market? Could the CAPM and Fama-French multifactor models give an resonable explanation to the value/growth effect? In order to explain the value/growth effect, the difference in expected returns of growth and value portfolios from asset pricing models should be close to the actual return differential. Furthermore, we also examine the significance of each factor by regressing it on the other factors. A significant regression alpha implies that the factor includes incremental information and should be added to the asset pricing model.

2. Is the growth effect a result of momentum? This question tests the importance of the momentum factor in explaining the growth effect in Vietnam.

3. Does momentum arise from the overreaction of investors? This question examines three main hypotheses explaining the momentum effect: underreaction, overreaction, and random walk.

4. Is the estimated measure of overreaction a predictor of Vietnamese stock returns? We build a measure of overreaction based on trading volume and the signs of stock returns. Consequently, this question tests the relation between the measure of overreaction and stock returns.

5. Does the momentum profit concentrate on stocks that have experienced a strong upward overreaction? The thesis sorts stocks by their past returns and levels of overreaction to investiage whether abnormal positive returns on the winners portfolios are actually concentrated in stocks with high measure of overreaction.

6. Does the trading strategy based overreaction provide higher adjusted returns than the trading strategy based on momentum? With this question, we make a comparison between returns of two trading strategies after adjusting for benchmark and for the asset pricing models.

7. Is there evidence of size effect in the Vietnamese stock market? In other words, do stocks with lower capitalization earn higher returns?

8. Is there any relation between size premium and default risk? We analyze the distress risk proxies of five size-ranked portfolios. There are two default-risk

proxies in the thesis: the debt-to-equity ratio and distance-to-default of Merton (1974).

9. Is the size premium concentrate on stocks with high default risk? If distress risk is the key reason for size premium, the higher the risk, the higher the average return for small stocks. Thanks to a triple-sorted technique, we divide every size-ranked portfolio into three sub-portfolios with virtually equal market capitalization but different distress-risk levels. The returns of sub-portfolios are compared to investigate whether the size premium is concentrated in the sub-portfolio with high default risk.

10. Is the explanatory power of size factor (the Small Minus Big - SMB factor) is adversely affected when the default-risk neutrality is applied in factor formation? With this question, we make a comparison of the explanatory power between the original size factor (Fama and French, 2016) and the size factor with default-risk neutrality.

1.3. The Vietnamese stock market

The stock market of Vietnam is officially established on 28th July 2000 with the birth of the Ho Chi Minh stock exchange. Initially, there are only four listed firms with a total capitalization of roughly $40 million. According to Nguyen et al. (2017), the market was in a nascent stage during 2000-2005. This period observes very few listings. In 2005, there are 44 listed firms with a total market capitalization of $300 million. In the period from 2005 to 2007, the market boomed. By virtue of the country's favorable economic conditions, the market capitalization rises rapidly to nearly $20 billion at the end of 2007. After a persistent and robust growth during the 2005-2007 period, the stock market of Vietnam is hit by the financial crisis (Nguyen et al., 2017). Consequently, numerous investors withdraw their funds from the market, which leads to a continuous and significant drop in stock prices during 2008-2009. Since the second half of 2009, the stock market of Vietnam has been gradually stabilizing thanks to the recovery of the Vietnamese economy.

The recent decade observes a substantial growth of the Vietnamese stock market. From a limited market capitalization of about $33 billion in 2009, the total market capitalization reaches roughly $186 billion at the end of 2020, which takes account for more than 68% of the national GDP. With the modern trading system and applications, the liquidity of Vietnamese stock market is also enhanced significantly. About 90% of transactions are conducted by automated order-matching systems. The total value of traded stocks rises rapidly, from nearly $8 billion in 2009 to about $56.9 billion in 2020. At the present, Vietnamese stock market is categorized as one of 23 emerging and frontier markets in the Morgan Stanley Capital International (MSCI). Vietnam ranks in the top 40 worldwide in terms of the market capitalization of domestic listed stocks according to the World Bank data. The Vietnamese capitalization is higher than several European markets such as Poland and Austria as well as New Zealand, a developed Pacific market.

Unit: billion$

Figure 1 - The market capitalization of Vietnamese domestic listed stocks from 2009 to 2020

Unit: billion$

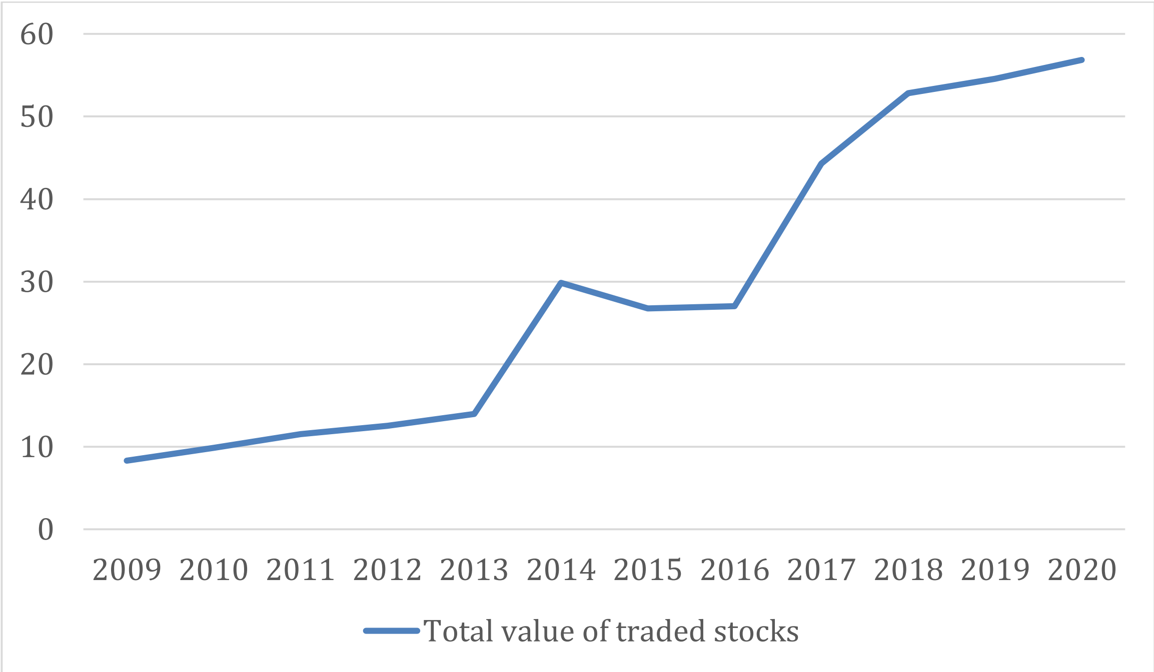

Figure 2 - The total value of Vietnamese traded stocks from 2009 to 2020

There are nearly one million local investors in comparison to about 20,000 foreign investors (Quach et al., 2019). The numbers of domestic and foreign institutional investors are around 9100 and 3000, respectively. Local investors currently own two-third of the total market capitalization. Based on data of 268 non-financial firms listed in the Ho Chi Minh stock exchange, the average ownership rate of domestic institutional investors is about 40% (Vo, 2016). Vietnam also attracts the attention of oversea investors thanks to a stable economic growth in recent years. On average, Vietnamese GDP increases by approximately 5.7% per year during 2009-2020, while the annual average global GDP growth is only around 2.5% according to the World Bank data. The Vietnamese inflation rate is controlled with a yearly average value of 2.8% over the 2013-2020 period. Furthermore, from 2016, foreign ownership in non-restricted firms is not limited at 49% as the prior period, which leads to a substantial increase in foreign portfolio investment (Vo and Truong, 2018). One-third of Vietnamese total market capitalization belongs to foreign investors. There are two exchange-traded funds (ETF) which specialize in the Vietnamese market: FTSE ETF listed in the London stock exchange and VNM ETF listed in the New York stock exchange (Quach et al., 2019). At the setup, their total assets under management are roughly $1 billion.

Comparing to developed markets, Vietnam has several unique characteristics. Firstly, Vietnamese investors are highly concerned about liquidity. In developed markets, most studies report a negative relationship between liquidity and stock' returns (Brennan and Subrahmanyam, 1996; Chordia et al., 2001; Amihud and Mendelson, 2008; Chiang and Zheng, 2015). This negative relationship means that investors should require higher rate of returns for holding illiquid stocks. In contrast, the return on Vietnamese stocks is positively correlated with the liquidity (Batten and Vo, 2014; Vo and Bui, 2016; Nguyen et al., 2019; Quach et al., 2019). By using an assorted number of liquidity measures, they show that investors do not require higher returns by holding illiquid stocks in Vietnam. In Vietnam, individual investors trade more frequently than institutional investors. Due to the dominance of small investors, their preferences towards shares of big corporations lead to an increase in demand for big and liquid stocks. Consequently, prices of liquid stocks are pushed up. Furthermore, thanks to the high level of trading activities over a period, stocks issued by big firms become visible and tradable to investors, which simulates the demand of these shares.

The second characteristic is the lack of available information. Many public firms including blue chips do not strictly follow the obligation of releasing financial statements. The legal system is not powerful enough to prevent firms from breaking publication regulations. Although listed firms must release their financial reports quarterly according to the regulation, a variety of them only publish their reports in 3 to 6 months later (Quach et al., 2019). Various Vietnamese companies only submit their financial statements to the stock exchange rather than publishing reports to their websites or other available sources. Recently, with stricter regulations as well as a stronger and better financial supervisory authority, the publication of annual reports for listed stocks is improved significantly (Vo, 2016). However, there is still a long pace for Vietnam to achieve the global financial standard as in developed economies.

The third unique characteristic is the short horizon of investment. Numerous Vietnamese investors focus more on short-run returns, instead of buying and holding stocks for a long horizon (Quach et al., 2019). Investors in Vietnam are still in the process of learning about stock investment knowledge and seem to be less rational. Odean (1998) suggest that less experienced investors are likely to be more overconfident in their ability and trade more frequently. Vietnamese investors have a tendency to hold stocks for only a couple of months. A very small number of them consider stocks as long-term investments or savings. Therefore, Vietnamese firms might change their characteristic group faster than firms in developed markets. A large firm could be ranked to the medium-sized or even small-sized group in the next quarter.

Although both Vietnam and China are socialist republic states, their government controls over stock markets are different in some extent. Firstly, the majority of Chinese listed companies are state-owned enterprises (Wang et al., 2019). Even worse, the Chinese government and these enterprises are most likely to make use of the external funds raised by listed companies in the post-acquisition stage to support and subsidize other inefficient state-owned corporations. Meanwhile, the proportion of Vietnamese stocks owned by state is only around 15%. There are only 71 out of 392 listed companies which have over 50% of their stocks owned by the Vietnamese government. Secondly, according to Wang et al. (2019), the Chinese equity market seems to be a policy-oriented market. Policies have long-term effects on the equity market and the government might intend to control the ups and downs of the market. Recently, due a new round of regulations proposed by the Chinese authority to control big technology companies, the stock prices of Alibaba as well as Tencent drops sharply. By contrast, financial markets in Vietnam are likely to be more liberal. From 2016, foreign ownership is not limited for non-restricted companies. The reform of regulatory bodies and financial institutional towards a sound financial system has been highly appreciated by international investors (Vo, 2016). Nguyen et al. (2017) even document that the monetary policy does not directly effect on the stock market except for the inflation. Hence, the government control does not have a significant impact on the Vietnamese stock market as the China.

1.4. Thesis structure

The thesis consists of seven chapters. Chapter 1 introduces the thesis, which includes motivation of the thesis, research questions, and an overview of the Vietnamese stock market.

The literature on the value/growth, momentum, and size effects is presented in Chapter 2, Literature review. To begin, the definition, assumptions, and three forms of the Efficient Market Hypothesis are summarized. Next, evidence of the value/growth, momentum, and size effects as well as different explanations for them are introduced.

Chapter 3, Data, explains the data collection for this thesis. This chapter is divided into three sections. In two first sections, sample stocks as well as the sample period are discussed. The final section introduces the market portfolio and risk-free asset for Vietnam.

In the succeeding chapters, our study therefore determines whether these effects exist in the Vietnamese stock market. Chapter 4, The growth effect in the Vietnamese stock market, firstly documents the existence of growth effect in Vietnam from 2009 to 2019. Secondly, it goes on to investigate whether the CAPM and Fama-French multifactor models can capture returns on growth and value stocks. Subsequently, the chapter examines the explanatory power of a three-factor model with momentum to the growth effect. It also tests three main hypotheses explaining momentum by tracking the momentum return up to 24 months following portfolio formation.

Chapter 5, Momentum and overreaction in the Vietnamese stock market, discusses a behavioral explanation to momentum in Vietnam. In the first place, the chapter reaffirms momentum in Vietnam during 2009-2019, even after excluding a period of bubble. Secondly, a measure of delayed overreaction in Vietnam is build based on trading volume and the sign of stock returns. By ranking stocks on their levels of overreaction, the chapter investigates whether stocks experiencing a stronger upward overreaction earn a higher average return. Finally, we estimate the benchmark- and risk-adjusted returns of trading strategies based on momentum and overreaction. If momentum arises from investors' overreaction, adjusted returns of momentum portfolios would be insignificant while adjusted returns of overreaction portfolios would be still significant.

Chapter 6, The size effect and default risk in the Vietnamese stock market, analyzes the relationship between size premium and bankruptcy risk. A size premium is well-documented in Vietnam over 2009-2019, even after adjusting for the bubble period. Then, two default risk proxies are estimated for all sample stocks: the debt-to-equity ratio and the distance-to-default. Stocks are triple-sorted on their risk proxies and capitalization to investigate whether abnormal positive returns on small portfolios are actually concentrated in high-risk stocks. Furthermore, the explanatory power of size factor is evaluated when the default-risk neutrality is applied in factor formation.

In the last chapter, Chapter 7, Conclusion, we summarize the empirical findings and draw key conclusions. A couple of limitations of this study are also acknowledged in this chapter.

2. Literature review

2.1. Efficient Market Hypothesis

An efficient stock market is initially defined as a market where stock prices all the time reflect all available information (Fama, 1970). In an efficient stock market, relevant information is rapidly impounded into the stock prices so that it is impossible for investors to make superior profits from their investment strategies. Efficient Market Hypothesis (EMH) has been the central proposition of finance for the next thirty years (Shleifer, 2000). It becomes a fundamental assumption for numerous financial theories. If the EMH is incorrect, various financial theories might be also inappropriate.

Since all available information at any point of time is incorporated in stock prices, they would be accurate estimates of their fundamental values. The fundamental value of an equity is the present value of all future dividends and capital gains, discounted in an appropriate rate. Obviously, in an uncertain world, the intrinsic values cannot be obsevered exactly, then the market price of an equity could be above or below its fundamental value. However, in an efficient market, market prices should not be driven far away from intrinsic values because whenever relevant news related to a firm hits the market, its stock price should instantaneously and precisely react to this news. The term "precisely" means that there is no underreaction or overreaction. Furthermore, when relevant news coming into the market is random and unpredictable, only current news would be reflected in current price changes, which are independent to past price adjustments. Thus, market prices should wander randomly around fundamental values, which leads to independent successive price changes. It is regarded as the random-walk theory of stock prices (Fama, 1965).

Shleifer (2000) states that the EMH is built on three main assumptions. Firstly, all investors in the market are rational and they evaluate every stock for its fundamental value, which equals the net present value of future cash flows. When relevant news hits the market, investors immediately and correctly react to this new information. Hence, stock prices incorporate all available information. Secondly, if several investors are irrational, they have a tendency to trade randomly. Their trading strategies seem to be uncorrelated, then their purchases should cancel out each other. As a result, stock prices should stand close to their fundamental values although there is a substantial trading volume among irrational investors. Thirdly, even if trading strategies of irrational investors are correlated, pushing stock prices far away from fundamental values; the arbitrageurs would eliminate the influence of irrational investors. For example, when a stock is overpriced, arbitrageurs would sell or short sell this stock and simultaneously buy a substitute security to earn profits. Due to this selling, the price of overpriced stock decreases to its fundamental value. Hence, the stock market is still efficient.

Fama (1970) distinguishes three forms of market efficiency. In the weak form, it should be impossible to systematically predict future price movements based on the past prices and returns. In the semi-strong efficient market, it is impossible for investors to earn excess returns using available public information such as the financial statements, news about mergers and acquisitions, etc. As soon as information becomes public, it is quickly incorporated in stock prices, then investors cannot gain using this information (Shleifer, 2000). In the strongest form, even the information from insiders of companies cannot help investors earn a superior risk-adjusted return since insiders' information immediately leaks out and is reflected in stock prices.

Jensen (1978) declares that the EMH dominates other financial theories with regard to the supporting empirical evidence. Many tests in the US stock market corroborate the weak and semi-strong forms of market efficiency. Fama (1965) states that the US stock prices between 1957 and 1962 follow random walks. There is no evidence of profit of trading strategies based on the past prices, such as purchasing stocks when their prices just went up. More complicated trading rules based on past returns also yield no profitability. Investigating 940 stock splits in the New York Stock Exchange from 1927 to 1959, Fama et al. (1969) find that on the average, the market's adjustments concerning the information implications of a split are fully reflected in the price of a share. The split causes price adjustments only to the extent that it is associated with changes in the anticipated level of future dividends. In other words, investors cannot earn superior risk-adjusted returns from the information implications of a split, which supports the semi-strong form of efficiency. Examining the price movements of 101 stocks of companies that are taken over on the New York and American Stock Exchanges in 1975-1978, Keown and Pinkerton (1981) show that the market reaction to intended mergers occurs before the first public announcement of the merger. However, the price movement on the announcement is not followed by a continued trend up or reversal down. Therefore, the market reaction to the new public information is complete by the day after the announcement, which does support the semi-strong efficient market.

Nevertheless, many academics and professionals are skeptical about the market efficiency. According to Grossman and Stiglitz (1980), as long as collecting private information is costly, stock prices cannot reflect all available information. In details, if securities prices reveal private information perfectly, investors who spend resources to obtain it would receive no compensation. They would do as well as investors who pays nothing for information. Consequently, all investors do not trade on the basis of private information, then the securities prices could not reveal any private information at all. Therefore, the informational efficiency of stock markets in the strong form as coined by Fama (1970) seems to be a precious fiction rather than reality. Furthermore, a variety of solid proofs contradicting to the EMH are revealed, which are regarded as financial market anomalies. The first anomaly is the momentum and reversal effect, challenging the weak form of efficiency. Reversal is the tendency for the stock return to be negatively correlated with its own lag, whereas momentum is the tendency for the stock return to be positively correlated with its past values. Evidence of momentum and reversal in the US stock market is discovered by De Bondt and Thaler (1985); Jegadeesh and Titman (1993). Consequently, this effect is found in many stock markets such as the US (Jegadeesh and Titman, 2001; Asness et al., 2013; Byun et al., 2016), Europe (Van Dijk and Huibers, 2002; Doukas and McKnight, 2005; Antoniou et al., 2007) and various emerging markets (Cakici et al., 2013; Hanauer and Linhart, 2015; Butt et al., 2021).

The semi-strong form of efficiency is also challenged by several anomalies. The size anomaly refers to high risk-adjusted returns for small size companies compared to big size companies. The size effect is documented in numerous developed as well as emerging markets such as the US, the UK, France, Japan, China, Korea, etc. (Banz, 1981; Reinganum, 1981; Keim, 1983; Lamoureux and Sanger, 1989; Van Dijk, 2011; Fama and French, 2016; Leite et al., 2018). In developed markets, investing in value shares tends to be more profitable than in growth shares, which is considered as the value effect. This effect is documented in the US market (McWilliams, 1966 and Basu, 1977) as well as many developed stock markets (Fama and French, 1998, 2017). Examining the US stock market during 1972-1980, Rendleman et al. (1982) discover the continual drifts in stock prices after annual earnings announcements. Then, the lagged reaction to earnings announcements is also documented by Cready and Gurun (2010), who find some evidence that the negative relation between earnings news and market return persists beyond the immediate announcement period in the US stock market between 1973 and 2006. In other words, these empirical results suggest that the market is not immediately fully impounding relevant news, contradicting the EMH.

Three anomalies that have attracted considerable attention among financial economists and practitioners are the value/growth, momentum, and size effects.

2.2. Value/growth effect

The value/growth effect is the difference of average returns between the value and growth stocks. Value stocks are stocks that have lower market prices relative to their fundamentals (book value, dividends, cash flow, earnings, etc.). The common characteristics of value stocks include a high book-to-market (B/M) ratio, high dividends yield, low price-to-earnings ratio (P/E), low sales growth rate, and/or high cash flow-to-price. The investors consider value stocks as cheap or undervalued stocks. Their past performance tends to be below-average and this trend is expected to continue in the future. Most value stocks are in distress with high leverages and low net incomes, which makes them “out of favor” by investors (Fama and French, 1998). In contrast, growth stocks, also known as glamour stocks, have higher prices relative to their fundamentals. They could be characterized by having a low book-to-market ratio, high price-to-earnings ratio, high sales growth, and /or low cash flow-to-price. They are considered as high prospective growth companies because they retain most of their earnings for reinvestment, therefore pay less dividends. The earnings and growth rate of growth companies are considerably higher than the market average. They are expected to continuously reach further in the future.

2.2.1. Empirical evidence of value/growth effect

In developed markets, investing in value shares tends to be more profitable than in growth shares, which is considered as the value effect. This effect is discovered in many markets over various periods. Initial studies are conducted by McWilliams (1966) and Basu (1977). Examining the US stock market between 1953 and 1964, McWilliams (1966) proves that investing in the value portfolio is better. 390 stocks are divided into deciles based on the price-to-earnings (P/E) ratio. The annual average return of the highest P/E portfolio is only 15%, while the yearly average return of the lowest P/E portfolio is nearly doubled, at about 30%. However, the standard deviations for two returns are almost equal, at roughly 30%. If the risk is measured by the standard deviation, the lowest P/E decile provides a significant superior return. Basu (1977) points out two main limitations in this research. Firstly, portfolios are formed before companies publish their income statements. It is known as the retroactive selection bias. To avoid this bias, Basu (1977) forms portfolios from the 1st of April, when the annual financial reports are available. Secondly, the standard deviation might not be an appropriate risk measurement. Hence, he utilizes the CAPM model to capture the market risk. Using data of 500 stocks listed in the New York Stock Exchange (NYSE) during 1956-1969, Basu (1977) discovers evidence of the value versus growth anomaly. He divides stocks into five portfolios by the P/E ratio. The low P/E quintile earns a yearly average return of 16.3% with a beta of 1.0413, while the high P/E quintile yields an annual average return of 9.34% with a beta of 1.1463. It is clear that high P/E stocks provide a lower mean return than low P/E stocks but are riskier in the sense of CAPM and beta.

Lakonishok et al. (1994) carry a study to examine the cross-sectional reationship between equity returns on a universe of NYSE and American Stock Exchange (AMEX) firms and five variables: past sales growth, book-to-price ratio, earnings yield, cash flow-to-price ratio, and size between April 1968 to April 1990. They conclude that both book-to-price and cash flow-to-price ratios on a standalone basis have statistically significant predictive power on returns. Notably, cash flow-to-price ratio appears to be the most significant variable. Stocks with higher cash flow-to-price deliver higher average returns.

Chan and Lakonishok (2004) investigate returns on benchmark indexes from Frank Russell Company that capture the performance of the 2,000 largest companies in the US. From 1979 through 2001, the spread in returns between value and growth portfolios is positive in 23 of 33 years, or 70% of the time. The value portfolio generates a geometric mean return of 14.74% per year. Compared with the geometric average return on the growth portfolio of 8.94%, the value stocks come out ahead by 5.8% a year.

Fama and French (2006) document a value premium in all stocks listed on the NYSE, AMEX, (after 1962) and NASDAQ (after 1972). The average value-minus-growth return is 0.35% per month for 1926 to 1963 and 0.44% for 1963 to 2004. The monthly average value premium for 1926 to 2004 is 0.4%, which equals 3.43 standard errors from zero.

Later on, evidence of the value premium in the US stock market is documented by Fama and French (2007a). The data are primarily from the Center for Research in Security Prices (CRSP) and Compustat. Their tests center on six portfolios ranked on size and B/M. In the sample period 1927-2006, the average continuously compounded annual returns for the Small-Value and Big-Value are 14.44% and 11.82%, respectively. By contrast, the Small-Growth and Big-Growth portfolios provide considerably lower average returns, at only 8.69% and 9.18% per year.

Similarly, based on the CRSP/Compustat merged database, Phalippou (2008) discovers that value stocks' average retum from 1980 to 2001 is 1.85% per month whereas growth stocks' average retum is 0.85%. Over the same period, the S&P 500 Index, as a benchmark, averages 1% per month and the risk-free rate averages 0.5%. The value versus growth anomaly is mainly a longside phenomenon or a value premium, not a shortside one or a growth discount. In other words, even investors do not short-sell growth equities, they still earn an abnormal return thanks to buying value equities.

Loughran and Wellman (2011) rank non-financial NYSE, AMEX, and NASDAQ stocks on their B/M ratios between June 1963 to June 2009. Then, they estimate the equal-weighted return for each B/M-sorted decile. The difference between returns on the high-B/M (or value) and low-B/M (or growth) deciles is 1% per month.

Based on data collected from the CRSP over the period 1972-2012, Hou et al. (2015) report that the value factor, a trading strategy that buys value stocks and sells growth stocks, earns an average return of 0.4% per month, with a t-statistic of 2.6. Dividing stocks in to 25 size-B/M portfolios, the high-minus-low B/M quintile earns an average return of 1.02% per month (t=4.59) in small stocks but only 0.16% (t=0.79) in big stocks.

Jaffe et al. (2020) document the value premim in all stocks for which Compustat and the CRSP provide sufficient data between July 1973 and June 2016. After sorting stocks into quintiles based on B/M ratio, they estimate the average value-weighted return on each quintile portfolio in excess of the 1-month Treasury bill rate. The average excess return of the highest B/M quintile is 0.75% per month, whereas the lowest B/M yields a monthly average excess returns of only 0.28%.

However, recent research shows that the performance of value investment in the US has become weaker than the previous period. Based on data obtained through the Ken French’s website, Israel and Moskowitz (2013) compute the CAPM alphas of the value factor during four 20-years sub-periods between 1926 to 2011. Although the alpha is always positive, it is only statistically different from zero in the 1970-1989 period. Using the US monthly data from the Ken French’s website and Bloomberg from 1962 through early 2014, Asness et al. (2015) document a considerable decrease in the Sharpe ratio of the value factor (the High Minus Low B/M - HML factor). The Sharpe ratios of the HML during 1971-1980 and 1981-1990 are 0.51 and 0.44, whereas these figures for 1991-2000 and 2001-2014 are substantially lower, at only 0.01 and 0.28. Kok et al. (2017) estimate the alphas from monthly market model regressions for the HML factor with data from the Ken French's website over 1926-2015. The annualized alpha for the 1982-2015 period is significantly positive, at 5.21% and t-statistic equals 2.97. By contrast, the annualized alpha for the 2002-2015 period is only 0.5% with a t-statistic of only 0.22, implying that the value premium becomes insignificant from 2002 to 2015. Similarly, Fama and French (2017) report that the average return of value factor in North America, which includes the US and Canada, is only 0.21% per month between 1990 and 2015. Its t-statistic is considerably low, at only 1.15.

A series of papers conducted by Fama and French (1998, 2006, 2012, 2017) demonstrate the existence of value premium on an international scale. According to Fama and French (1998), the value portfolio provides an excess return in 12 out of 13 stock markets over 1975-1995. The average differential between returns on international value and growth portfolios is 7.68% per year. Using merged data for 14 markets outside the US collected from MSCI, Fama and French (2006) construct value-weighted size-B/M portfolios. The overall value-weighted international value premium is 0.53% per month during the period 1963-2004, which is 2.63 standard errors from zero. In three regions (Europe, Japan, and Asia Pacific), there are value premiums in average stock returns between November 1990 and March 2011 (Fama and French, 2012). Recently, stock returns in 23 developed markets in four regions from 1990 to 2015 are also taken into account (Fama and French, 2017). In all regions, the value premium is significantly positive with a high t-statistic, except for North America. The highest value premium belongs to the Asia Pacific, at 0.59% per month; while monthly value premiums for Europe and Japan are almost equal, at 0.32% and 0.36% respectively.

Evidence of the value effect is also discovered in developed European countries. The data sample of Bird and Casavecchia (2007) is constituted by almost 8,000 stocks from 15 European countries between January 1989 and May 2004. The value portfolios outperform the growth portfolios irrespective of ranking stocks by B/M ratio, P/E ratio, or sales growth rate. Investigating all listed UK firms from 1987 to

2001, Dissanaike and Lim (2010) state that the portfolio strategy based on the B/M ratio yields mean a risk-adjusted return of 0.77% per montth in the frameworrk of the Fama-French three-factor model. In other words, a trading strategy, which is long value shares and short growth shares, provides a significant risk-adjusted return in the UK. Daniel and Chris (2014) focus on all stocks that are constituents of the MSCI Europe Index during January 1990 to April 2010. The annualized spread return between the high-B/M amd low-B/M portfolios is 8.92% with a t-statistic of 1.84. After subtracting transaction costs, this annualized spread return is still substantially high, at 7%.

However, the value/growth effect is significantly different among emerging stock markets. Cakici et al. (2013) find strong evidence for the value effect in 18 emerging markets in three regions: Asia, Latin America, and Eastern Europe between 1990 and 2011. The value factor in Eastern Europe earns the highest mean monthly return, at 1.88% with a t-statistic of 3.6. According to Hanauer and Linhart (2015), the value factor is substantial and significant for 21 emerging markets over 1996-2012, with an average of 0.93% per month. It is nearly as twice as high for the global portfolio with a value of 0.47%. Ebrahim et al. (2014) reaffirm the presence of value premium in three emerging markets: Brazil, Turkey, and China from 1999 to 2009 with significant and positive returns of the value minus growth portfolios. However, the value minus growth in India provides a negative return, at -1.05% per month, which implies that growth stocks outperform value stocks in India. This result is consistent with Leite et al. (2018). Their data sample includes listed companies in 12 emerging countries during 2007-2017. The difference between the returns on diversified portfolios of value and growth stocks is significantly negative in Argentina, India, Thailand, Romania, and Russia. To illustrate, in Romania, growth shares generate a 1.53% average monthly return higher than value shares. In other words, in these countries, growth stocks outperform value stocks, which is contrary to the value effect in developed stock markets. Hence, the pattern in stocks' returns in several emerging markets might not follow the same trend found in developed markets.

2.2.2. Explanations of value/growth effect

The value/growth effect is recognized as one of the biggest challenges to practitioners and academics, many hypotheses are advanced to explain this anomaly. There are two main types of explanation: risk-based and behavioral points of view.

From the risk-based point of view, abnormal returns on value stocks are compensation for bearing a higher risk level, consistent with rational and eficient pricing in equity markets. According to Fama and French (2004), from 1926 to 1963, betas of value stocks in the US market are considerably higher than growth stocks, which implies a higher systematic risk. In the post-1963 period, since the CAPM is unable to explain the value effect, Fama and French (1993) develop the three-factor model. They declare that value firms tend to be engaged in some sorts of financial distress. If a value company goes bankrupt, shareholders would not receive any payment, leading to a high-risk level of holding value stocks. Fama and French (1993) regress monthly stock returns against the returns of a market portfolio and returns of portfolios built to mimic the risk factors in returns related to size and B/M equity risk factors. Generally, the Fama-French three-factor model captures much of the variation in the cross-section of equity returns and absorts some anomalies unexplained by the CAPM. It suggests an equilibrium asset pricing model and provides that B/M ratio and size proxies for common risk factors in returns. In 2016, Fama and French extend the three-factor model by adding profitability and investment factors. Thanks to two new factors, the five-factor model is able to explain returns on the Small-Growth stocks, which cannot be captured by the three-factor model (Fama and French, 2017). Griffin and Lemmon (2002) investigate the relationship between financial distress risk, B/M ratio, and stock returns in the US between 1965 and 1999. There are more growth (low B/M) firms than value (high B/M) firms in the group of firms with the highest distress risk. Additionally, these value stocks with highest distress risk earn an extremely low average return, at only 6.36% per year, slighly lower than the risk-free rate of return in the sample period. Thus, the presumption that the value premium is compensated for default risk should be rejected, which is in line with Groot and Huij (2018). Analyzing the US market in 1991-2012, they report that high-risk value stocks provide a lower return than low-risk value stocks. It suggests that the value premium is unlikely to be attributed to distress risk.

Several other papers also explore the risk-based explanation. According to Zhang (2005), value firms scale down more than growth firms in recessions, and growth firms invest more in expansions. Meanwhile, reducing capital leads to higher costs than expanding capital. In bad times, value firms are burdened with more unproductive capital. Due to higher ratios of fixed assets to total assets and higher financial leverage, it is more difficult for value companies to reduce ineffective capital than growth companies (Gulen et al., 2008). Consequently, their dividends and returns would covary more with economic downturns. In expansions, growth firms invest more and face higher adjustment costs to take advantage of favorable economic conditions. As expanding capital is relatively easier than reducing capital, their dividends and returns do not covary much with economic upturns. The net effect is a high dispersion of risk between value and growth strategies in economic downturns and a low dispersion of risk in economic upturns. Hence, investing in value stocks is riskier than in growth stocks, at least in the adverse states of the world. The economic fundamentals of value firms respond negatively to economic shocks, whereas the same does not hold for growth stocks (Petkova and Zhang, 2005). Chan and Lakonishok (2004) also document that value stocks underperform growth stocks during the technology bubble era of 1996-1999. Andrew (2014) states that the value premium exists since it is the compensation for losses during bad times. Examining the value strategy in the US from 1965 to 2010, he shows that value stocks outperform growth stocks over the long run. However, there are several notable periods when value stocks procedure losses such as the recession in the early 1990s or the roaring Internet bull market during the late 1990s. In the financial crisis over 2007-2008, the value strategy also leads to large losses. During bad times, the betas of value stocks rise significantly, which causes value firms to be particularly risky. If an investor cannot afford to shoulder the losses generated by value stocks during bad times, he cannot harvest the value premium. Garcia-Feijoo and Jorgensen (2010) find positive associations between book-to-market and the degree of operating leverage, between operating leverage and systematic risk in the US between 1987 to 2003. It indicates that the systematic risk associated with firm-level investment activity is the key determinant of the value premium.

Attempts to explain the value premium by macroeconomic risks have limited success. Despite time-varying risk goes in the righ direction in explaining the value premium in the US during 1927-2001, the estimated covariation between the value-minus-growth betas and the expected market risk premium is insufficient to explain the value premium in the conditional CAPM (Petkova and Zhang, 2005). Based on the US data from 1927 to 2005, Cooper and Gubellini (2011) vary the conditioning variables used to estimate the risk level of value portfolios in the conditional CAPM. Among expected market risk premiums that they examine, only one specification gives consistent results with the risk-based explanation. The other specifications result in insignificant beta-premium differences between value and growth stocks. According to Fong (2012), the value premium in the US between 1952 and 2009 cannot be captured by macroeconomic risks. Obtaining nominal GDP and CPI forecasts from the Livingston Survey[1], Fong (2012) builds a time series of expected real GDP growth and employs it as a risk factor. While expected real GDP growth could predict stock market returns in a direction that is in line with a risk-based explanation, no similar evidence holds for HML portfolios. In the conditional CAPM, the betas of HML portfolios are negative in both economic upturns and downturns. Average returns of value stocks are nearly the same across all economic states, then the value premium seems to irrelevant to risk compensation. A similar empirical result is reported by Hwang and Rubesam (2013), who estimate the regime-swithing CAPM for the US portfolios over 1963-2008. All three risk measures do not support that the value portfolio is riskier than the growth. The CAPM beta is neagtive for the HML portfolio. The value premium exists even without operating leverage or an industry-wide investment effect (Guthrie, 2013). Although both operating

[1]Livingston Survey is the oldest continuous survey of economists' expectations in the US, which summarizes the forecasts of economists from industry, government, banking, and academia. It is available from: https://www.philadelphiafed.org/surveys-and-data/real-time-data-research/livingston-survey

leverage and industry-wide investment weaken the value premium, these effects cannot eliminate the superior returns of value stocks.

The second group of explanations is based on the irrational behavior of investors. A number of studies provide empirical evidence that relies on behavioral finance paradigm and some forms of market inefficiency to give alternative explanations behind the value/growth effect. The behavioral explanation is initially revealed by Lakonishok et al. (1994). They state that growth companies are forecasted to be fast-growing and highly profitable in the future, which represents a good investment. Hence, due to extrapolating prior earnings growth far away into the future and considering growth firms as good investments regardless of their prices, various investors tend to be excessively optimistic about growth stocks and bid them up. Consequently, growth stocks appear to be overpriced. As time passes, prices of growth stocks are much higher than their fundamentals but their growth and profits seem to decrease because of two reasons (Fama and French, 2007a). The first reason is the pressure of competition and regulation. Secondly, they exercised most of their profitable options. As a consequence, the returns on growth stocks fall considerably. By contrast, value companies performed below-average with low net incomes in former times. Then investors become overly pessimistic about value stocks and try to pay as little as possible for their shares. As a result, value stocks are oversold, which makes them become underpriced. Meanwhile, value firms have an opportunity to enhance their performance and restructure, which leads to better-than-expected profits. Over the long time, stock prices move toward their intrinsic values, then value stocks outperform growth stocks. According to Fama and French (2007a), value portfolios generate substantially larger capital gain returns than growth portfolios in the US over 1927-2006. Meanwhile, the dividend contribution for both value and growth stocks are nearly the same. Based on a universe of NYSE and AMEX firms over 1968-1990, Lakonishok et al. (1994) analyze the actual future growth rates and compare them to past growth rates and expected growth rates as indicated by the valuation multiples (ex: B/M, P/E) accorded by the equity market. Growth stocks have historically grown faster in sales, earnings, and cash flow than value stocks during the five years before portfolio formation. The large differences in the valuation ratios between the value and growth portfolios imply that the market expects the superior patterns of growth stocks to continue into the foreseeable future. However, over the five post-portfolio formation years, the actual growth rates of value firms are generally higher relative to the actual growth rates of the growth stocks. Hence, investing in value shares yields higher returns than in growth shares because the actual future growth rates of sales/earnings/cash flows of growth stocks relative to value stocks turn out much lower than they were in the past or as the market expectation. Furthermore, the market appears to consistently overestimate the future growth rates of growth stocks and underestimate value stocks, which is known as mispricing.

Additionally, Ackert and Deaves (2010) point out two more behavioral reasons why most institutional investors overvalue growth stocks and spend a great deal of fund in them. Although being aware of the anomaly, institutional investors may still avoid investing in value stocks due to their career concerns. Firstly, sponsors consider firms with steady earnings and buoyant growth as prudent investments. Following their fiduciary obligation, institutional investors have to act prudently. Meanwhile, value stocks are viewed as hard-to-defend and out-of-favor. As a result, institutional investors tend to stay away from value firms. Secondly, since being often evaluated once a year, they might be nervous about tilting too far in any direction, thus incurring tracking error. A value strategy would require such a tilt and may take some time to pay off, which may lead to poor evaluation for institutional investors. Given this backdrop, various institutional investors are prone to growth firms when forming their portfolios, which leads to the existence of value/growth anomaly.

The behavioral explanation is consistent with the findings of La Porta (1996), Zou and Chen (2017), who examine the analyst' forecasts of future earning rates for growth and value portfolios in the US market during 1982-1990 and during 1990-2013. The analyst' forecasts are proxied by IBES forecasts from the Institutional Brokers' Estimate System. The analyst' forecasts of future earning rates for growth (value) stocks turn out to be much higher (lower) than the actual earning rates, which indicates that analysts overestimate the future earnings rates of growth stocks relative to value stocks. On the other hand, Mian and Teo (2018) do not detect any significant differences in the magnitude of the average optimistic bias between forecasts of Japanese growth and value stocks from 1991 to 1999. The forecasts of value firms even tend to be more optimistic in comparison to those of growth firms. It is inconsistent with Lakonishok et al. (1994). Daniel et al. (2001) declare that investors' overconfidence induces overreaction (see section 2.3.2), then the overreaction to private signals causes the value effect. Piotroski and So (2012) divide the US companies into two groups over the 1972-2010 period. Among those firms where expectations implied by current prices are incongruent with the strength of their fundamentals, the value/growth effect is strongest. However, among firms whose fundamental strength is congruent with expectations, the value/growth effect is approximately zero. Hwang and Rubesam (2013) state that substantially positive average returns on the value-minus-growth portfolio arise from the correction of mispricing. Due to a higher uncertainty of value stocks, the correction is more severe for them than for growth shares. It is the reason why about 80% of the value premium in the US during 1963-2008 comes from value rather than growth shares. Based on the mispricing estimation method of Rhodes-Kropf et al. (2005), Jaffe et al. (2020) construct the mispricing factor, which is the return differential between undervalued and overvalued stocks. The value premium in the US market between 1973 and 2016 completely disappears when the mispricing factor is added to the asset pricing model. Furthermore, the mispricing factor subsumes the value factor according to the framework of Barillas and Shanken (2017). Hence, mispricing can explain the value premium in the US, consistent with the behavioral explanation.

2.3. Momentum effect

The momentum effect is the positive relation between a stock's return and its previous performance. It suggests that shares with high past returns during a medium period (from three to 12 months) would generate a high return subsequently, while stocks with low past returns would continue falling. In other words, momentum is the tendency of stocks' performance over the next medium-term horizon to be predictable from their relative performance in the past three to 12 months. To investigate the momentum effect, stocks are divided into the winner and loser. Stocks with the highest average past returns are put into the winner portfolio, while stocks with the lowest average past returns are assigned into the loser portfolio.

2.3.1. Empirical evidence of momentum effect

There is much evidence of the momentum effect in the US stock market. The pioneering work is carried out by Jegadeesh and Titman (1993). Analyzing the US market between 1965 and 1989, they sort stocks each month into deciles based on performance over the past j months (with j ranging from three to 12 months). The top decile of performers is dubbed as the winner, whereas the bottom decile of performers is dubbed as the loser. Then, they create overlapping portfolios that hold these stocks for the next k months (with k ranging from three to 12 months) (overlapping technique is explained in section 5.3.3). Trading strategies that purchase the winner and sell the loser provide substantial abnormal returns. For example, the documented average profit is 12.01% per year when both j and k equal to 6. Chan et al. (1996) rank the US stocks by their compound returns over the prior six months and assign them into deciles from 1977 to 1993. During the first year after portfolio formation, the annual average return of the winner decile is 29.7%, which is nearly doubled the average return of the loser decile (14.8%). Evidence of momentum over 1963-1994 is also discovered by Asness (1997). His data sample includes all common stocks in the New York Stock Exchange, American Stock Exchange, and NASDQ stock exchanges. Shares are divided into quintiles based on the average monthly return during the past 12 months. The monthly average returns of the winner and loser portfolios are 1.48% and 0.61%, respectively. The difference in returns between the winner and loser is significant, at 0.87% per month with a t-statistic of 3.73. Similarly, Jegadeesh and Titman (2001) find that the difference between winner and loser portfolio returns is about 1.23% monthly over the period 1965-1998. With a universe of 724 largest US firms from 1972 to 2009, Asness et al. (2013) state that the momentum premium is statistically significant, at

7,7% yearly with a t-statistic of 2.84. However, since 2000, the momentum strategy fails to generate significant abnormal returns. Creating a monthly dataset of the US security prices during 1801-2012, Geczy and Samonov (2016) document more than 200-year history of momentum profits, averaging around 0.4% monthly. From 1801 to 1926, the monthly average return of momentum strategy is 0.28%, compared with 0.58% for the 1927–2012 period. Using simultaneous monthly return observations of the US equities over 1965-2014, Pukthuanthong et al. (2018) state that momentum yields a Sharpe ratio of about 0.5, which exceeds a reasonable bound. As a consequence, it could be considered as an abnormal profit opportunity. The sample of Byun et al. (2016) includes all stocks traded in the NYSE, AMEX, and NASDQ between 1965 and 2009. Although the monthly return differential between the winner and loser portfolios is 0.95% with a t-statistic of 3.66 during 1965-2009, in the sub-period of 2000-2009, this figure decreases to -0.32%. Chen and Lu (2017) report that the momentum strategies deliver inconsiderable profits for the 1996–2011 period. The momentum return is only marginally significant with a t-statistic of 1.78 when j=6 and k=1. It is consistent with Bhattacharya et al. (2017), who show that the monthly momentum return in the US declines to an insignificant level of 0.69% in the period 1999-2012. There could be several possible reasons for the declining momentum profits in the US. Firstly, more and more investors become increasingly aware about the profitability of implementing a relatively simple momentum trading strategy. The growing awareness and competition amongst these investors lead to a reduction in return continuation in the holding period. Secondly, market efficiency in the US seems to improve significantly. Bhattacharya et al. (2017) record a fairly considerable decrease in the degree of response of stock returns to past market returns after 1998.

The momentum effect is also uncovered in various developed markets in Europe. Investigating common stocks in 15 European markets from 1987 through 1999, Van Dijk and Huibers (2002) assert that momentum strategies are profitable in the sample period for holding periods of one month up to 12 months. For the 12-month holding period, the momentum strategy earns the highest return, at 11.8% per year. This strategy still yields an annual risk-corrected return of 9.9% in excess of an equally weighted index in the full sample period. Van Dijk and Huibers (2002) calculate the average B/M ratio and the average market cap for mometum-styled portfolios. While an almost perfectly linear negative relationship between price momentum and B/M is revealed, no linear negative relationship between average market cap and price momentum is apparent. Consequently, momentum is a different phenomenom from value and size anomalies. Likewise, Doukas and McKnight (2005) state that momentum in stock returns has persisted in eight out of 13 European markets during the period 1988–2001. Germany observes the largest momentum profit, at approximately 1.21% per month with a t-statistic of 3.65. According to Antonio et al. (2007), between 1977 and 2002, the momentum strategy generates statistically significant monthly profits of 2.10%, 1.82%, and 1.44% for the UK, Germany, and France, respectively. A high portion of momentum profits comes from the loser portfolio, except for France. Fama and French (2012) do 2 x 3 sorts on size and past returns to create the momentum factor for 15 European markets between 1990 and 2011. The monthly average return of momentum factor is significanly positive, at more than 0.9% with a t-statistic of 3.38. Based on European stock data from January 1988 to December 2013, Huhn and Scholz (2019) construct a zero-investment portfolio that buys recent winner stocks and sells recent loser stocks according to past raw returns. Although it exhibits strong return reversals in the first two weeks after portfolio construction, they find the momentum patterns over weeks 4-52. This trading strategy delivers a positive and significant performance in terms of mean returns and risk-adjusted returns within the framework of Fama-French three-factor model.

Evidence of momentum is not only found in developed markets but also emerging markets. According to Griffin et al. (2010), momentum strategies provide positive returns in 12 out of 16 emerging countries during 1994-2005. Although momentum returns are statistically significant in both developed and emerging markets, they are somewhat lower in emerging markets. The richer the country, the higher momentum return. Following the method of Fama and French (2012), Cakici et al. (2013) build the momentum factor in 18 emerging markets of Asia, Eastern Europe, and Latin America over 1990-2011. They report that this momentum factor yields considerably positive average returns in Asia and Latin America, at 0.93% and 0.96% per month, respectively. If the three emerging regions are included together, the monthly average return of momentum factor is 0.86% with a t-statistic of 2.02. Hanauer and Linhart (2015) also document a strong momentum effect in BRIC (Brazil, Russia, India, and China) and Asia from 1996 to 2012. The mean returns for momentum factor in the two regions are both significant, at 1.07% and 0.94% per month. Overall, the momentum factor has the monthly average return of 0.97% (t-statistic = 1.97) in 21 emerging markets classified by the MSCI Index. The momentum premium presents in big stocks, then it is not driven by the size effect. Recently, Butt et al. (2021) revisit the momentum profit in 19 emerging markets from 1991 to 2017. Momentum returns are positive for 13 countries, of which five countries exhibit significant returns (Brazil, Chile, India, Pakistan, and South Africa). The highest memntum profit belongs to India, at 2.421% per month with a t-statistic of more than 4.3.

Despite the broad evidence of momentum profits around the world, there is several remarkable exceptions. The monthly average return of momentum factor in Japan over 1989-2011 is only 0.08%, with a t-statistic of 0.25 (Fama and French, 2012). According to Asness et al. (2013), the performance of the winner and loser portfolios in Japan between 1974 and 2011 are nearly the same, at around 9% per year. Similarly, Hanauer (2014) cannot find a premium for the momentum factor in Japan during 1986-2012. There is an inconsiderable monthly momentum profit of only 0.02% that is not significantly different from zero (t-statistic = 0.06). Hanauer (2014) declare that momentum returns are significantly higher when the market remains in the same condition than when it reverses to another state. Meanwhile, market transitions occur more frequently in Japan in comparison to the US, leading to the empirical failure of momentum in Japan. The momentum return is considerably negative in Argentina and Turkey between 1994 and 2005 (Griffin et al., 2010). Cakici et al. (2013) show that the momentum factor yields a negative return of -0.25% per month in five emerging Eastern European markets from 1990 to 2011. Additionally, six countries namely Turkey, Malaysia, Greece, South Korea, Indonesia, and Philippine observe a negative momentum return over the period of

1991-2017 (Butt et al., 2021). Turkey observes the poorest performance of momentum strategy, at -1.233% per month with a t-statistic of -2.26. Thus, the loser outperform the winner in Turkey.

2.3.2. Explanations of momentum effect

Despite the solid empirical evidence of momentum in many equity markets over different periods, there are ongoing debates among researchers and academics with regard to the sources of momentum profit. The risk-based point of view cannot give a reasonable explanation of the momentum profitability. The Fama-French three-factor model is unable to capture the momentum profitability in the US (Fama and French, 1996; Grundy and Martin, 2001). According to Wang and Wu (2011), only about 34% of the raw momentum returns in the US over 1965-2002 can be explained by the Fama–French three-factor model. Based on the US daily returns from the CRSP database for the years 1960 through 2009, Yu (2012) shows that the momentum strategy generates a significantly positive risk-adjusted return of 0.24% per month within the framework of Fama-French three-factor model and Carhart four-factor model.

Momentum is also not driven by industry risk or business cycle variables. Grundy and Martin (2001) estimate the returns to a strategy of purchasing firms in industries that were winners over the six months and shorting an equal dollar amount of firms in the loser industries. The industry momentum strategy does not exhibit the level of profit earned by the total momentum strategy in the US in the period 1962-1995. While the total momentum strategy yields 1.59% per month, the comparable number for the industry strategy is only 0.55%. Therefore, the industry effect is unlikely to be the primary cause of momentum. Chordia and Shivakumar (2002) use the dividend yield of market index, default spread, term spread between ten-year Treasury bonds and six-month Treasury bills, and short-term interest rates to measure market conditions. This set of business cycle variables can explain profits of momentum strategies in the US from 1952 to 1994. However, according to Cooper et al. (2004), a multifactor macroeconomic model of Chordia and Shivakumar (2002) has no ability to forecast the time-series of momentum profits following bull markets during 1929-1995. Its ability to explain the momentum profit is not robust. Similarly, Geczy and Samonov (2016) declare that individual macroeconomic variables do not explain momentum in the US from 1801 through 2012. Liu and Zhang (2008) use the growth rate of industrial production as a common macroeconomic risk factor driving stock returns. Investigating stocks listed in the NYSE, AMEX, and NASDQ over 1960-2004, they report that over half of momentum profits is explained by this risk factor. Nevertheless, the risk factor of Liu and Zhang (2008) is no longer priced in the 1999-2012 period (Bhattacharya et al., 2017).

Conrald and Kaul (1998) declare that the momentum profit simply reflects cross-sectional variability in average returns. According to their hypothesis, winners should continue to outperform losers in any post ranking period. Their basic argument can be overturned by the empirical results of Jegadeesh and Titman (2001), who point out that losers earn significantly higher returns than winners after one year of portfolio formation. Booth et al. (2016) demonstrate that the size effect appears to dominate the price momentum effect in the US from 1962 to 2013. Since the small-firm effect is a proxy for risk, they propose a risk-based explanation for the momentum effect. However, as mentioned in section 2.4.2, the literature is inconclusive on the source of size effect, then the conclusion of Booth et al. (2016) might be inappropriate.

From the behavioral explanation, a large number of studies postulate that the underreaction and overreaction of investors causes momentum. Barberis et al. (1998) argue that many investors mistakenly conclude that stocks realizing extraordinary performance will continue to produce similar extraordinary performance in the future, known as representative heuristic. Beside, the conservatism bias suggests that investors underestimate new information in updating their priors. It leads to underreaction to information and slow incorporation of information into stock prices, creating momentum. Hong and Stein (1999) consider two types of investors: news-watchers and momentum traders. News-watchers obtain private information about future cash flows but ignore information about past prices. If information diffuses gradually among investors, the information obtained by news watchers is only partially incorporated in stock prices, which is considered as the underreaction. Hence, momentum traders might earn profits by trend-chasing. Their momentum trading strategy leads to the eventual overreaction in a median run, followed by reversals when momentum traders close out their positions. Hong et al. (2000) obtain the analyst coverage, which is the number of analysts observing a particular equity, for NYSE, AMEX, and NASDAQ stocks in 1976-1996. Obviously, information of stocks with lower analyst coverage would be spread more slowly. Since analyst coverage is very strongly correlated with firm size, they regress the analyst coverage against the size and a NASDAQ dummy variable to estimate the residual analyst coverage. They discover that the momentum strategy provides higher returns among stocks with low residual coverage. The momentum profit in the low-residual-coverage subsample is 1.13% per month, whereas this figure is 0.72% in the high-residual-coverage subsample. Hence, stocks with slower information diffusion tend to exhibit more pronounced momentum, consistent with Hong and Stein (1999). Doukas and McKnight (2005) document a similar result in 13 European markets from 1988 to 2001. The momentum trading strategy generates a 0.88% per month average return (with a t-statistic of 3.22) for the subsample of low coverage stocks. By contrast, it earns an monthly average return of roughly 0.6% for the high-residual-coverage stocks. Examining the earnings suprises in each momentum-styled portoflio in Europe, Van Dijk and Huibers (2002) report that analysts' forecasts are extremely optimistic for the losers and are extremely pessimistic for the winners. Futhermore, the largest downward earnings-forecast revisions are made for the losers and the largest upward earnings-forecast revisions are made for the winners, indicating that price momentum is caused by slow incorporation of earnings-related news. Chen and Lu (2017) find that momentum profits in the US during 1996-2011 are larger for stocks whose information diffuses slowly into the stock market, consistent with Barberis et al. (1998); Hong and Stein (1999). Chen and Lu (2017) argue that for winner (loser) stocks, if prices of call options increase (decrease), it implies that informed option traders believe that the positive (negative) information associated with those winner (loser) stocks has not been fully incorporated in the stock prices.

Hence, they buy winner stocks with the highest growth in call option prices and sell loser stocks with the largest reduction in call option prices to enhance the stock selection based on information diffusion speed. This enhanced momentum strategy provides a monthly risk-adjusted return of 1.78%, while the return of standard momentum strategy is insignificant.

Daniel et al. (1998) declare that numerous investors have a tendency to overestimate their ability to obtain private information and underestimate their forecast errors. These investors are known as overconfident investors. Some of their predictions might be appropriate when public information signals arrive, which increases their level of confidence due to biased self-attribution. As a result, overconfident investors continue overreacting to private information. Continuing overreaction causes momentum in share prices in a short period. However, over the long term, securities prices would be adjusted to their fundamental values, leading to long-term reversals. There is empirical evidence supporting Daniel et al. (1998). The positive relation between the momentum profitability and the proxies of investor overconfidence is reported in several papers. Overconfident investors tend to trade excessively, leading to extremely high trading volume. Lee and Swaminathan (2000) state that past trading volume forecasts both the persistence and magnitude of momentum profits in the US during January 1965 through December 1995. Additionally, over the third year through the fifth year after portfolio construction, initial winner portfolios substantially underperform initial loser portfolios. It suggests that at least a portion of the initial momentum gain is characterized as an overreaction. According to Cooper et al. (2004), from 1929 to 1995, the average monthly momentum profit in the US is significantly positive (negative) following positive (negative) market returns. Momentum profits are reversed in the long term, as predicted by the overreaction theories. Furthermore, Hwang (2010) finds that the momentum effect in the US would increase if the correlation of investors' forecast errors is higher, which is consistent with the prediction of Daniel et al. (1998). According to Hanauer (2014), if the stock market stays in the same condition, the predictions of overconfident investors are more likely to be accurate, investors' overconfidence would be expected to be higher.

Thus, the momentum profit would be higher if the market remains in the same state. Analysing the Japanese market during 1986-2012, he discover that following past bear markets, the monthly averagre momentum return is 2.35% per month when the subsequent market is down and −2.88% when the subsequent market is up. Similarly, after bull states, the monthly mean momentum return is 1.40% when the market remains unchanged and −1.35% when a market transition occurs. These findings are in line with Daniel et al. (1998). Using the signed trading volume to measure continuing overreaction, Byun et al. (2016) point out that continuing overreaction is better than the past return in predicting future returns in the US stock market from 1965 to 2009. A strategy, which is long shares with upward continuing overreaction and short shares with downward continuing overreaction, earns a considerably positive profit of 1% per month. Although the returns of trading strategies based on momentum and overreaction are virtually equal, the Sharpe ratio of overreaction strategy is considerably higher thanks to a lower standard deviation. Using a new measure that directly captures the speed with which stocks react to firm-specific information, Hur and Singh (2016) assert that momentum profits in the US over 1990-2014 are consistent with behavioral models' predictions regarding investors' overreaction.

Tracking the momentum profit in the long-run may help shed better light on momentum. If momentum arises from the pure underreaction to information, information would be gradually incorporated in stock prices. Then, when stock prices fully reflect all information, the momentum profit would be zero in the long term. By contrast, if continuing overreaction to information causes momentum, in the long horizon, stock prices would be corrected to their intrinsic values, leading to negative momentum returns or reverals. Thirdy, if the rationales behind momentum are expected returns that vary with past returns, momentum profits would be followed by zero returns in subsequent periods. Analysing the stocks listed on the NYSE, AMEX, and NASDAQ between 1965 and 1998, Jegadeesh and Titman (2001) present cumulative momentum profits over a five-year post-construction period. Althought the monthly average profit in the first year is 1.01%, the average return from the second to fifth year is -0.26% per month, which is reliably less than zero.

This empirical result corroborates the overreaction story. Similarly, according to Chan et al. (1996), the momentum return in the second and third years after portfolio formation is negative. Their data sample covers all stocks traded on the NYSE, AMEX, and NASDAQ during 1977-1993. Over the second to third year following portfolio construction, the average return of a strategy, which is long the winner decile and short the loser decile, is only -0.3% per year. Recenly, Conrad and Yavuz (2017) track the momentum profit up to five years after portfolio formation based on a universe of NYSE, AMEX, and NASDAQ firms from 1965 to 2010. They only discover a considrable reversal in the second year with a significant negative momentum return of -0.36% per month (t-statistic = 3.63). Form the third to fifth year, the momentum strategy yeilds negative return, though not significant. More importanly, 56% of individual stocks that contribute to momentum profits do not experience long-run reversals. In other words, instead of securities that experience momentum being more likely to reverse, the stocks that do not contribute to momentum are more likely to experience reversals. The findings of Conrad and Yavuz (2017) are in line with the pure underreaction.

Although the above work gives evidence supporting the behavioral explanation, there are still several unanswered questions (Subrahmanyam, 2018). How representative heuristic and conservatism bias of Barberis et al. (1998) affect investment decisions in reality? Could we separate out the new-watchers and the momentum traders, then obsever whether they actually trade in the manner suggested by Hong and Stein (1999)? Do investors really exhibit self-attribution bias in the long term proposed by Daniel et al. (1998)? Among three explainations of Barberis et al. (1998), Hong and Stein (1999), and Daniel et al. (1998), which of these theories are more consistent with data?

Another behavioral explanation is the disposition effect of Shefrin and Statman (1985). High past stock returns lead to pride accompanying the realization of paper gains. Thanks to realizing paper gains, investors may be trading more after high stock returns, which pushes stock prices to an unduly level. Hence, momentum exits in an intermediate period. Examining stocks traded on the NYSE and AMEX over 1967-1996, Grinblatt and Han (2005) declare that a variable proxying for unrealized capital gains appears to be the key variable that drives the profitability of momentum strategy. However, their inference can be overturned. Dispositon effect only explains the superior returns of winners. According to the disposition effect of Shefrin and Statman (1985), investors may be trading less after negative stock returns, because they do not want to sell securities and acknowledge the loss, thus reducing the trading volume of losers. However, not only winners but also losers experience high trading volume (Jeffrey et al., 2009; Byun et al., 2016).

2.4. Size effect

The size anomaly refers to the negative relation between the security returns and the market value of the common equity. In other words, it refers to high average stock returns for small size companies compared to big size companies. The small (big) size companies are companies which have small (big) market capitalization. The capitalization is measured by multiplying the price and the number of outstanding shares.

2.4.1. Empirical evidence of size effect

This phenomenon was first addressed by Banz (1981), who show that small-capitalized firms on the New York Stock Exchange earn higher average returns than is predicted by the CAPM from 1926 to 1975. Investing in stocks with the lowest capitalization may lead to an excess return of 0.4% per month, which is higher than other stocks. The size effect is not linear in the market capitalization, the key effect focuses on very small stocks while there is little return differential between medium and big stocks. Later on, the size premium in the US stock market is reaffirmed in various periods: 1963-1977 (Reinganum, 1981); 1963-1979 (Keim, 1983); 1973-1985 (Lamoureux and Sanger, 1989).

Reinganum (1981) divides a universe of nearly 600 stocks traded in the NYSE and AMEX into 10 portfolios based on their capitalization. Then, excess returns are computed by subtracting the daily return of the equal-weighted NYSE-AMEX index from the daily portfolio return. This index is also used as the market portfolio to estimate betas. Between 1963 and 1977, the daily average return of decile with the highest market value is -0.03%, whereas the comparable number for the smallest decile is 0.05%. Meanwhile, the difference in estimated betas seems to be insufficient to explain the return diferential. Estimated betas for the biggest and lowest deciles are 0.82 and 1, respectively.

Keim (1983) examines the anomalous negative relation between firm size, measured by total market value of common equity, and average returns for the sample of NYSE and AMEX firms over 1963-1979. He also ranks stock into deciles. While the average market value of equity for the smallest is only $4.4 million, the average market cap for the largest is more than $1 billion. On average, the portfolio of smallest firms generates approximately 20.7% per annum, which is much higher than the return implied by its beta risk. In contrast, the annual average return of biggest firms is less than -9%.

Based on data of 7.659 stocks quoted on the NASDAQ system over the period from 1973 through 1985, Lamoureux and Sanger (1989) rank all firms by market value of outstanding equity and assign them into 20 portfolios. They discover an obvious evidence of a size anomaly for NASDAQ equities. Monthly mean returns decrease almost monotonically from 3% for the smallest size-ranked portfolio to 1% for the biggest size-ranked portfolio. Both the beta and standard deviation cannot give a plausible exlplanation to the return differential between the smallest and largest portfolios. The estimated betas for both portfolios are close to 1 and the monthly time series standard deviations are around 3%.

Fama and French (1992) divide all stocks traded in the NYSE, AMEX, and NASDQ over the period 1963-1990 into 12 portfolios on the basis of ranked values of capitalization. They find that the average return of the smallest portfolio (1.64% per month) is significantly higher than the average return of the largest portfolio (0.9% per month). Although stocks in the smallest decile have higher betas that that of the largest one, this risk difference is not enough to explain the difference in average returns. This result is similar to previous studies investigating the US market between 1960s and 1980s.

However, the size effect in the US stock market seems to disappear after the early 1980s. Specifically, Chan et al. (2000) and Horowitz et al. (2000) report that small equities do not outperform big equities during the 1980s and 1990s. According to Chan et al. (2000), for the 15-year period between 1984 and 1998, the average return on the Russell 2000 Index of small-cap stocks is 11.22% per annum, in comparison to 17.71% for the Russell 2000 Index of large-cap stocks. Horowitz et al. (2000) examine the relation between expected return and firm size for data from the NYSE, AMEX, and NASDAQ in 1980–1996. The yearly compounded return for the smallest decile is roughly 15%, compared to slightly over 16% for the biggest size decile. Since the average slope on the natural logarithm of market capitalization is not statistically different from zero, monthly regressions show no systematic relation between expected return and size return. Thus, the size premium tends to vanish since 1980.

Van Dijk (2011) analyzes the annual value-weighted return differential between the smallest and biggest size quintiles of all NYSE, AMEX, and NASDAQ stocks during 1927–2010. For the entire period, this differential amounts to 6.7%. Nevertheless, in 38 out of 84 years, small-cap stocks underperform large-cap stocks, especially in the periods 1946–1957 and 1980–1999. In the 2000s, the size premium comebacks with an average value of more than 11% per annum.

Fama and French (2012) report that there is no size premium in 23 developed countries from 1990 to 2011. The average returns of size factor in four regions (North American, Europe, Japan, and Asia Pacific) are all close to zero. Asia Pacific observes the lowest size premium, at less than -0.2% per month.

After collecting stock data for firms listed on the FTSE All-Share Index, Hwang et al. (2014) test the size effect in the UK over 1985-2012. Stocks are placed into quintiles (or deciles) from the smallest to the biggest portfolio. For the whole period, the smallest quintile earns a monthly average return of about 1.33%, whereas the average return for the largest is only 0.83%. In the sub-period from 2000 to 2012, the smallest portfolio with a monthly return of 1.58 % is the best performing portfolio and the largest portfolio is the worst performing portfolio.

Hur et al. (2014) document a strong size effect in the US over July 1931 through December 2006. The mean return for the decile with the smallest securities is close to 2% per month, roughly three times higher than the mean return of 0.60% for the decile with the securities with the largest capitalization. As the firm size progressively declines across deciles, the average return rises.

Groot and Huij (2018) investigate the size effect in a universe of the 1.500 largest US stocks by monthly ranking them on their market capitalization and calculating the equal-weighted returns over the subsequent month. Between 1991 and 2012, the smallest quintile outperforms the biggest quintile with an insignificant 1.7% per year. Compared to the value premium of 5.3% per annum, the size premium seems to be considerably smaller.

Investigating stocks traded on the main exchange of 16 European countries between 1990 and 2013, Muns (2019) only finds the size premium in the financial industry. While risk-adjusted returns decline monotonically with size in the financial industry, this pattern is absent in other industries. The risk-adjusted return difference between the two most extreme size groups is significant only in the financial industry, at 0.63% per month with a t-statistic of 3.78.

According to Hou and Van Dijk (2019), although the size premium in the US is significant for 1963-1982, at more than 10% annually, the size premium in the US is essentially zero for 1983-2014. For 1983–2014, the average excess returns are 0.60% per month for the smallest size decile and 0.62% for the largest size decile. More interestingly, the size effect in developed European markets and Japan is economically large and statistically significant before 1983, but negligible after 1983, which is similar to the US. It is consistent with Fama and French (2017), who declare that the 1990-2015 size premium is close zero in the North America and Europe. Similarly, a weak size premium of 0.34% per month with a t-statistic of 1.7 is documented in Japan during 1963-2014 (Cheema et al., 2021). In 1963-1983, this monthly size premium is close to 0.9%, but it drops dramatically to -0.01% in 1983-2014. However, Hou and Van Dijk (2019) find a strong size effect in an international sample of 22 developed and 19 emerging stock markets over the 1965–2014 sample period and little evidence that it disappears after the early 1980s. From 1985 to 2014, the trading strategy, which is long the smallest decile and short the biggest decile in a global sample, yields a monthly average return of 1.1%, with a t-statistic of 4.88. Hence, they conclude that a large size premium is still present in global stock markets in recent decades.

Evidence of the size effect is documented in many emerging markets. According to Barry et al. (2002), mean returns for small firms exceed mean returns for large firms in 35 emerging stock markets with the sample period spanning January 1985 through July 2000. The monthly average returns decrease across size categories, from 2.94% for small firms to 0.74% for large firms. However, the size effect is not robust to removal of extreme returns for emerging market equities. Cakici et al. (2013) declare that the size factor provides considerably postive returns in 13 emerging markets in Asia and Latin America from 1990 to 2011. To illustrate, the monthly average return of size factor in eight Asian countries is 0.42%, with a t-statistic of 1.98. Similarly, there is empirical evidence that suggests the existence of size effect in nine out 12 emerging markets between 2007 and 2017 (Leite et al., 2018). The highest size premium belongs to China, at 1.36% per month, with a t-statistic of more than 3. Small companies have lower average returns than big companies only in Argentina, Turkey and Russia.

The stock price is used as a common factor in computing the market capitalization and valuation ratios to investigate the size and value/growth effects. Hence, it is reasonable to infer that there is an interaction between two effects. According to Fama and French (2004), most value firms have small market capitalization and vice verse, growth stocks are usually large-size stocks. In a series of papers conducted by Fama and French (2007a, 2012, 2016, 2018), we always observe a stronger value effect among small firms. For example, Fama and French (2007a) divide all the US stocks during 1927-2006 into six groups based on their market cap and B/M ratios. The return differential between the Small-Value and Small-Growth is 5.74% per annum, whereas the return differential between the Big-Value and Big-Growth is only 2.6%. Similarly, according to Fama and French (2018), a trading strategy, that buys value stocks and sells growth stocks in a universe of small stocks in the US over 1927-2016, yields 0.51% per month with a t-statistic of 2.96. In contrast, the comparable number for a universe of large stocks is only 0.19%

with a t-statisc of 1.57. Several studies have attempted to find which effect - value/growth or size, is more predominant.

Reinganum (1981) argues the superiority of size effect in the US for 1963-1977. The value effect disappears after controlling portfolio returns for market values. To illustrate, in the smallest quintile, the growth (high-P/E) stocks possess a 0.017% higher daily retunrn than the value (low-P/E) stocks. By contrast, the strong size effect still emerges after controlling returns for value effect.

Basu (1983) declares that the size effect seems to be of secondary importance in comparison with the value effect in the US market over 1963-1979. In all five size classes, the value stocks yield higher risk-adjusted returns than their growth couterparts. However, the size premium virtually disappears when returns are adjusted for differences in risk and P/E ratios.

According to Fama and French (1992), although both the B/M ratio and size are significant variables to explain the cross-sectional variation in stock returns in the US for 1963-1990, the B/M ratio is likely to play a larger role than size. As previously discussed, the size premium vanishes after 1980s. By contrast, although being weaker in recent decades, the magnitude of the value premium is somewhat higher than the size premium. Analyzing the US market between 1927 and 2016, Fama and French (2018) report that the monthly average return of value factor is 0.35%, whereas the size factor delivers 0.26% per month. Likewise, Groot and Huij (2018) find a value premium of 5.3% per year, approximately three times higher than the size premium of 1.7%.

Meanwhile, the interaction between the size and momentum effects in the US is different in two sub-periods (Alhenawi, 2015). In the subsample during 1963-1993, momentum is stronger among smaller firms (Hong et al., 2000; Alhenawi, 2015). However, between 1994 and 2012, the momentum effect is stronger in larger firms (Alhenawi, 2015). There is a spread of 0.72% per month between the winner and loser portfolios in the smallest size quintile. In the largest size quintile, the corresponding spread is substantially higher, at 1.60% per month.

2.4.2. Explanations of size effect

Despite solid proof of the size effect in many equity markets, academics as well as practitioners remain inconclusive about the source of superior returns on small stocks. There are several explanations of the size effect.

The first explanation is due to the risk level. By examining the structural characteristics in the US from 1956 to 1985, Chan and Chen (1991) declare that low-cap companies often have inferior production efficiency and high leverage, which implies higher default risk. Furthermore, over 50% of firms that have cut their dividends in half or more in the last year are in the bottom size quintile. Meanwhile, companies that cut their dividends substantially are likely to perform poorly and face a very uncertain future. Thus, investing in small shares leads to a higher risk level. A market index heavily weighted toward large firms cannot capture the risk of holding smaller stocks, then the size premium cannot be expained by the CAPM as documented by Banz (1981), Reinganum (1981), and Lamoureux and Sanger (1989). Since a three-factor model with the market, size, and value factors capture a vast majority of variability in the US stock returns over 1963-1991, the size might be a proxy for distress risk (Fama and French, 1996). The effect of bankruptcy risk on stock returns is evaluated by Vassalou and Xing (2004). They use the Merton's (1974) option pricing model to estimate default measures for the US individual firms over 1971 through 1999. As the size premium is only documented in the highest risk quintile and smaller companies have considerably higher distress risk, they conclude that default risk accounts for the size effect. According to Hwang et al. (2010), the CAPM augmented with a credit spread factor that represents distress risk could explain the size effect in the US from 1934 to 2006. Because of high slopes to the credit spread factor, small-cap stocks are more sensitive to changes in the excess credit spread. The size premium could be attributed to the undiversifiable credit spread that is closely related to the default risk. Using data from the UK stock market in 1985–2012, Hwang et al. (2014) apply the Markowitz efficient frontier to build a portfolio performance measure that compares the actual return of a portfolio to its optimal return. Their findings suggest that the size premium appears to be associated with a higher level of diversifiable risk. Muns (2019) argues that investing in big European financial firms leads to a lower average return than in small financial firms due to the fact that large financial institutions are protected from tail events by governments. Therefore, in recessions, small financial firms are faced with higher distress risk.

On the other hand, many papers question the risk-based explanation. Using accounting models to measure default risk, Dichev (1998) reports that low-risk stocks deliver higher average returns for the period 1981 to 1995 in the US. The monthly average return of firms with the highest probability of bankruptcy is lowest, at only 0.48%, whereas the comparable number for firms with the lower probability of default is more than 1%. Hence, the default factor is improbable to be the source of size premium, which is similar to the conclusion of Campbell et al. (2008). He measures the premium for financial distress in the US over 1981-2003 by sorting stocks according to their failure probabilities. Although financially failure stocks have higher slopes on the size factor in comparison to those with lower distress risk, they do not provide higher returns. The mean returns for the highest-risk of stocks are considerably negative, at −16.1% per annum. By contrast, the 5% lowest-risk stocks deliver a positive annual average return of over 3%. Hur et al. (2014) contend that if distress risk accounts for the size premium, in down markets, risk-averse investors would bid down the prices of high-risk securities, leading to low returns for small stocks. However, since the size premium is significantly positive only in down markets and is estimated to be zero in up markets, the relationship between size and returns comes entirely from economic downturns. Thus, payment to size does not represent payment to distress risk. Recently, Groot and Huij (2018) show that the size premium in the US cannot be explained by bankruptcy risk irrespective of estimating the default probability by accounting and structural models, credit ratings, or credit spread. Low-risk small-size stocks earn up to 6% higher annualized average returns than high-risk small-size stocks. If small firms run more distress risk than large firms, they should underperform big firms in economic downturns. However, it appears that small stocks do not only outperform big stocks during expansions, but also during recessions. Furthermore, the explanatory power of size factor to stock returns is not attributed to distress risk.

A second plausible explanation is due to the liquidity risk. Stoll and Whaley (1983) find that it is impossible to earn abnormal risk-adjusted returns on small stocks after accounting for transaction costs in a sample of firms listed on NYSE over the period 1960-1979. For the smallest firms, the commission rate on a turnaround transaction averages 3.84%, while for the largest firms, the turnaround commission averages 2.02%. Pastor and Stambaugh (2003) create a liquidity measure based on stock returns and trading volumes in the US between 1962 and 1998. According to their measure, smaller stocks are less liquid and portfolios of small firms have the highest loadings on the liquidity factor. However, they contend that the relationship between the size premium and illiquidity is not straightforward since the liquidity betas do not declines progressively across size deciles. Similarly, investigating all common shares listed in the New York Stock Exchange and American Stock Exchange over 1962-1999, Acharya and Pedersen (2005) find that small stocks have lower average liquidity and higher exposures to three liquidity risk factors. According to Pastor and Stambaugh (2003); Acharya and Pedersen (2005), the liquidity risk factors improve the explanatory power of asset pricing models for small portfolios. Unfortunately, they do not investigate whether liquidity risk absorbs the size effect.

Thirdly, the size effect can be attributed to the extraordinary performance of small caps in January. Keim (1983) shows that a large part of the size premium in the US during 1963-1979 is due to a return differential of no less than 15% between small and large stocks in January. Much of this difference originates from the first five trading days. Similarly, according to Lamoureux and Sanger (1989), January's return exceeds the returns in all other months of the year. The monthly average return of the smallest decile is significantly positive in January, at 13.3%; but negative from February to December, at -11.5%. Investigating all firms listed in the NYSE, AMEX, and NASDAQ over the period 1927-2010, Van Dijk (2011) finds that the return differential between the smallest and the largest size quintile is around 5% in January and is approximately zero in all other months. Identically, according to Hur et al. (2014), most of the size effect in the US from 1931 to 2006 is concentrated in January. In January, returns are high for small firm securities regardless of the market state. The retun differential between the smallest and largest decile is statistically significant, at 10.12%. Meanwhile, this return differential is no longer significant if all non-January months are taken into consideration. There are two key reasons why small stocks outperform big stocks in January. The first reason is the tax-loss selling hypothesis. To take advantage of tax benefits, at the end of the year, individual investors have an incentive to sell shares that have experienced large price declines. At the beginning of the new year, prices recover thanks to the absence of selling pressure. Roll (1983) reports a negative relation between stock returns in January and returns over the previous year in the US over 1963-1980, which is consistent with the tax-loss selling hypothesis. A similar relation in the US between 1963 and 1999 is documented by Grinblatt and Moskowitz (2004). However, Chen et al. (2007) find no relationship between the size effect and January effect for the UK during the period 1955 to 2003. It suggests that taxes cannot be the entire explanation. The second reason is the window dressing hypothesis. Since being often evaluated once a year, institutional investors have an incentive to buy winners (or growth and big stocks) and sell losers (or value and small stocks) at the end of the year. Early in January, they rebalance their portfolios in favor of more speculative securities such as value and small stocks. Ng and Wang (2004) investigate the institutional holdings of common stocks traded on NYSE, AMEX, and NASDAQ in 1986-1998. Institutions sell approximately 27% more extreme loser small stocks in the final quarter of the year than in other quarters. By contrast, in the first quarter, their net holdings of small stocks rise by 22%. Analyzing the trading data of 841 different institutions over the period 1999-2005, Lynch et al. (2014) show that pension funds tend to sell small stocks with poor past performance during the final trading days in December, which provides some supports for the window dressing hypothesis.

Another possible explanation to the size effect is the extreme return. Using the Fama and French (1992) data, Knez and Ready (1997) remove the extreme 1% of the observations. After excluding extreme returns, small portfolios earn negative returns. For example, in the high-B/M quintile, the raw average return of small portfolio is 1.76% per month. This return drops substantially to -0.02% when Knez and Ready (1997) trim the extreme observations. Furthermore, the Fama–MacBeth regressions do not yield a significantly negative coefficient on firm size. Instead, they find a positive coefficient of 0.3 with a t-statistic of 7.32. Similarly, based on a universe of stocks traded in NYSE, AMEX, and NASDAQ from 1926 to 2005, Fama and French (2007b) state that the size premium is almost entirely generated by small-cap stocks that earn extreme positive returns and move to a big-cap portfolio from one year to the next. However, both papers do not explain why these small stocks deliver extreme positive returns.

3. Data

3.1. The sample period

The 2009-2019 period is chosen because of three main reasons. Firstly, both the number of listed stocks and market capitalization in the pre-2009 are relatively small. From only 250 listed stocks in 2008, this number increases rapidly to 338 stocks in 2009. More importantly, when many large Vietnamese companies become listed in 2009, the stock market really represents the Vietnamese economy (Quach et al., 2019). In 2008, the total market capitalization is $12.3 billion, which takes account of 12.47% of the national GDP. In 2009, the capitalization goes up to $33.3 billion, which accounts for 31.42% of the GDP. Secondly, prior to 2009, the financial reports of some listed firms are likely to be manipulated due to the weak regulation as well as the inadequate audit system. Several listed companies, especially small and medium-sized companies, make adjustments to their financial statements to meet investors' demands. For example, according to its annual reports, the net profit of Kinh Do Corporation in 2007 is about $7 million. However, the audited reports in 2008 imply that this corporation has an actual loss of $3 million. Since 2009, with stricter decrees issued by the Ministry of Finance regarding the accounting system and the development of independent audit companies, the manipulation in financial statements is significantly prevented. Finally, a stock market speculative bubble builds up in Vietnam during 2005-2007. During this period, stocks are considered as very attractive investments and numerous Vietnamese investors continuously purchase more stocks with a huge volume. The Vietnamese market index rises sharply from only around 300 in 2006 to nearly 1200 in 2007. At the same time, the Vietnamese GDP growth rate in 2007 is only 7.13%. Therefore, the substantial increase in stock prices seems to be unreasonable and could be regarded as a stock market bubble, which bursts in 2008. Being affected by the financial crisis in 2008, stock prices considerably drop and most investors oversell their shares. By March 2009, the market declines 80% from its peak in 2007. There could be a great amount of noise in data in the pre-2009 period. Only after the second half of 2009, the stock market of Vietnam has been gradually stabilizing thanks to the recovery of the Vietnamese economy. Given these reasons, the chosen period is between July 2009 and June 2019.

3.2. Sample stocks

There are two stock exchanges in the Vietnamese stock market: Ho Chi Minh stock exchange and Hanoi stock exchange. However, most stocks listed in the Hanoi stock exchange belong to medium and small-sized firms, then their stock prices are very likely to be manipulated. The regulations and lifetime of Hanoi stock exchange are shorter than Ho Chi Minh nearly ten years. Therefore, investigating stocks listed in the Hanoi stock exchange does not help understanding well how investors actually value shares in Vietnam. The thesis focuses on the Ho Chi Minh stock exchange, accounting for more than 90% of the Vietnamese market capitalization.

The data sample includes all non-financial shares in the Ho Chi Minh exchange. According to Fama and French (1992), the high leverage of financial firms does not have the same meaning as non-financial firms. For non-financial firms, high leverage more likely implies a higher default risk. Hence, financial stocks are excluded in most papers applying Fama-French asset pricing models. Furthermore, as mentioned in chapter 6, if the sample includes financial firms, they would be classified as firms with high distress risk although their actual default risk might not be high, which leads to the bias in ranking stocks on risk proxies. All commercial banks, insurers, and securities corporations are considered as financial companies, then their shares are excluded from the data sample. Sample stocks do not delist or relist over 2009-2019.

Stock prices are collected from DataStream through Thomson Reuters Eikon. The access is granted by the Aix-Marseille School of Economics. Collected prices are the closing prices or stock prices at the end of trading days. They are adjusted for the dividends, stock splits or similar corporate actions by DataStream.

	Ho Chi Minh stock exchange	Hanoi stock exchange
Year of establishment	2000	2007
Requirements for new listed companies	Having operated in the form of Joint Stock Company for at least 2 years	Having operated in the form of Joint Stock Company for at least 1 years
	Being profitable for two consecutive years	Being profitable for the last year
	A minimum chartered capital of about 6$ million	A minimum chartered capital of about 1.5$ million
	Publishing information about internal debts.	No regulation
Daily trading limit	7%	10%
Average capitalization	&74.7 billion	$4.68 billion

Note: the average capitalization for each stock exchange is calculated between 2009 and 2020.

Figure 3 - Several characteristics of Ho Chi Minh and Hanoi stock exchanges

Prices of Vietnamese stocks which are infrequently traded are likely to be manipulated (Quach et al., 2019). Hence, to reduce the impact of non-trading bias, if a stock is not traded in more than ten continuous business days, it would be omitted from the sample. Additionally, because the daily trading limit for Ho Chi Minh stock exchange is 7%, if the absolute value of a weekly return is more than 35%, it should be considered as an irrational return or a noise. To eliminate noises, all weekly stock returns which are above 35% or below -35% are also removed.

The accounting data for listed firms is gathered from a combination of DataStream and Fiingroup. The accounting data in DataStream between 2010 and 2019 is adequate, but during 2008-2009, there are several missing observations. Therefore, the second source of data is Fiingroup, a leading financial data provider in Vietnam. Then, two databases are compared and matched. Overall, the accounting data for listed firms from both databases are identical. However, there are slight differences in the accounting numbers of some companies, especially small firms in 2010 and 2011. Most of them are initially published, then their financial reports may not be standardized. Therefore, these firms are excluded from the sample. For missing observations in DataStream during 2008-2009, the accounting data is only collected from Finngroup if it is audited by an independent audit company. If financial reports are not audited, they are also excluded from the data sample. The number of sample stocks in each period is outlined in Figure 4. The total number of non-financial listed stocks in Ho Chi Minh stock exchange is presented in the second column. The next three columns give the number of excluded stocks due to differences in accounting data, extreme returns, and non-trading days. The final column shows the actual sample size for each period.

Year	Listed stocks	Differences in accounting data	Extreme returns	Non-trading stocks	Data sample
2009	129	1	2	2	124
2010	204	7	6	4	187
2011	235	8	6	5	216
2012	254	2	7	7	238
2013	258	3	4	3	248
2014	262	2	6	4	250
2015	273	3	2	3	265
2016	284	3	0	2	279
2017	312	2	3	3	304
2018	325	2	1	3	319
2019	348	0	3	5	340

Figure 4 - Data collection

3.3. The market portfolio and risk-free asset

The market portfolio is the VN-Index, a capitalization-weighted index of all the companies listed on the Ho Chi Minh stock exchange. It implies the variation of all stocks listed in this stock exchange. The index is created with a base index value of 100 as of July 28, 2000. Data of VN-Index is also collected from DataStream.

Since this research is conducted in the Vietnamese context, the one-year Vietnamese government bond is considered as the riskless asset. Thanks to being issued by the Vietnamese State Bank, it virtually has no default risk. In several studies, the US Treasury Bill is regarded as the risk-free asset for emerging markets. However, because the inflation rate in Vietnam is usually much higher than in the United State, the US Treasury bill rate appears to be insufficient to compensate for inflationary risk in Vietnam. Hence, the yield on a one-year Vietnamese government bond is likely to be a more reasonable risk-free rate in Vietnam. It is obtained from Thomson Reuters Eikon.

The VN-Index is used to calculated the Vietnamese broad market return and the yield on one-year Vietnamese government bond is also used as the proxy for riskless rate in some papers such as Nguyen at al. (2017), Quach et al. (2019), and Vo and Phan (2019).

4. The growth effect in the Vietnamese stock market

While there is empirical evidence of the value effect in various developed stock markets, the growth effect is documented in Vietnam. On the one hand, the CAPM and Fama-French models cannot capture Vietnamese growth and value stock returns. Three out of four mimic factors do not contain incremental information on expected returns. On the other hand, a three-factor model with the momentum factor gives an appropriate explanation of the growth effect. Both robustness tests demonstrate the explanatory power of this three-factor model. Furthermore, the delayed overreaction is likely to be the key source of momentum in Vietnam. Taken together, the superior return on growth portfolio arises from the momentum effect in which investors tend to overreact to information of the past return. It is consistent with the behavioral explanation.

4.1. Introduction

Over recent decades, empirical proof of the value effect, which is the tendency of value stocks to provide excess returns compared to growth stocks, has been reported in various markets. The term "value and growth" becomes a prominent label in the financial lexicon. Although the value effect is comprehensively investigated in developed markets, there is a small number of papers for Vietnam, one of the most dynamic markets in Asia. Vietnam ranks in the top 40 worldwide in terms of capitalization of domestic listed firms and attracts a huge amount of international investments. Its total capitalization is approximately $180 billion, with one-third belonging to foreign investors. Moreover, a few studies for the Vietnamese market provide different empirical findings. While Nguyen et al. (2015) declare a value premium of 0.61% per month, Quach et al. (2019) discover evidence of a growth effect rather than a value effect. Hence, this chapter's first goal is to examine the returns on value and growth stocks in Vietnam. Over ten years between 2009 and 2019, growth stocks earn superior returns compared to value stocks. On average, the growth portfolio's annual return is more than 12.4%, whereas the yearly return on the value portfolio is only 7.2%.

The second goal is to explain the superior returns of Vietnamese growth stocks. The CAPM and Fama-French (FF) multifactor models cannot capture returns on growth and value stocks. Three out of four FF mimic factors do not include additional information on expected returns according to the redundancy test of Barillas and Shanken (2017). Therefore, the FF models seem to have limited explanatory power to Vietnamese stock returns. By contrast, a model including the market, size, and momentum factors, gives an appropriate description of stock returns. Because of high exposure to the momentum factor, the growth portfolio's superior return arises from the momentum effect. Furthermore, by tracking the momentum return up to 24 months following portfolio formation, we reveal that the delayed overreaction is the main source behind the momentum effect. According to Vo and Phan (2017), herding exists in Vietnam. Most growth stocks are issued by big and highly profitable firms that attract Vietnamese investors (Vo and Bui, 2016). Thus, investors tend to overreact to the good news about their prior stock returns, which bids their stock prices up. It is the key reason why the growth portfolio outperforms other portfolios. In terms of the robustness, both the redundancy test and the GRS test prove the three-factor model's explanatory power with momentum.

There are several value-enhancing aspects in the field of market finance. Firstly, this chapter contributes to the literature on value and growth stocks in emerging markets. While evidence of the value effect is reported in numerous developed and international markets, the growth effect is discovered in Vietnam. It shows that a strong return pattern found in developed stock markets might be inaccurate in emerging markets. Secondly, this paper investigates how multifactor asset pricing models perform in Vietnam. Then we examine relevant factors that could be used to calculate expected returns on Vietnamese stocks. Thirdly, there are also some contributions to the literature investigating the momentum effect. Although the momentum effect in Vietnam is discovered by Vo and Truong (2018), they do not explain this effect. In this chapter, three alternative explanations are evaluated by tracking the momentum return following portfolio formation.

There are six sections in this chapter. The next section presents the literature overview. Data sample and methodology are clarified in the third and fourth sections. The fifth section reports empirical findings. Conclusions are drawn in the final section.

4.2. Literature Review

Generally, growth stocks are relatively expensive compared to their accounting figures, such as sales, book value, net income. According to La Porta (1996), these companies' earnings and growth rates are considerably higher than the market average. They are expected to reach further in the future continuously. By contrast, prices of value stocks are lower than their fundamental factors. The past performance of value firms is below-average, and this trend is forecasted to continue in subsequent periods. Stocks are classified into value and growth groups by comparing the market stock price and its fundamental factors. Stocks with high price-to-value ratios are often labeled as growth stocks, whereas value stocks have considerably lower P/E (price-to-earnings) or M/B (market-to-book) ratios.

In developed markets, investing in value shares tends to be more profitable than in growth shares, considered the value effect. This effect is discovered in many markets over various periods. Initial studies are conducted by McWilliams (1966) and Basu (1977). Examining the US stock market, they state that high-P/E shares generate substantially lower returns compared to low-P/E shares over two different periods: 1953-1964 and 1957-1971. According to Fama and French (1998), the value portfolio provides an excess return in 12 out of 13 stock markets from 1975-1995. The average differential between returns on international value and growth portfolios is 7.68% per year. Recently, stock returns in 23 developed markets in four regions from 1990 to 2015 are also considered (Fama and French, 2017). The value premium is significantly positive in all regions with a high t-statistic, except for

North America. The Asia Pacific, which includes Australia, New Zealand, Hong Kong and Singapore, has the highest value premium, at 0.59% per month.

Although there has been considerable research on growth and value stocks in various markets, there is little published research in Vietnam. Despite not directly investigating the value effect, Nguyen et al. (2015) provide empirical proof of a value premium during 2007-2015. On average, monthly returns on low- and high-M/B portfolios are 0.48% and -0.04%, respectively. The average value premium is 0.61% per month. In contrast, Quach et al. (2019) point out a growth effect rather than a value effect after examining data of 60 biggest Vietnamese firms between 2010 and 2014. On average, the high-M/B portfolio earns a 2.7% higher monthly return than one with low M/B does. Several caveats apply to these findings. Firstly, due to a great amount of noise in stock prices in the pre-2009 period (see section 3.1), Nguyen et al. (2015) 's findings might be inaccurate. At the same time, the sample of Quach et al. (2019) includes only 60 biggest firms, then many small and value companies are ignored. Secondly, both papers do not give explanations of returns on growth and value shares. Thus, it is necessary to comprehensively investigate the performance of growth and value investment strategies in Vietnam.

To capture the returns on value and growth stocks, several asset pricing models could be used. According to Fama and French (2004), from 1926 to 1963, betas of value stocks in the US market are considerably higher than growth stocks, which implies a higher systematic risk. In the post-1963 period, since the CAPM cannot explain the value effect, Fama and French (1993) develop their three-factor model. They declare that value firms tend to be engaged in some sorts of financial distress. If a value company goes bankrupt, shareholders will not receive any payment, which indicates a high-risk level of holding value stocks. It leads to the FF three-factor model in which the M/B ratio and size represent unobservable common risk factors. During 1963-1993, the US portfolios' returns ranked on P/E ratios, price-to-cash flow ratios, and sales growth are completely described by the three-factor model (Fama and French, 1996). Fama and French (2016) extend the three-factor model by including investment and profitability factors. Thanks to these factors, the five-factor model can explain returns of small-growth firms, which is unable to be described by the three-factor model (Fama and French, 2017). Given this backdrop, the CAPM, FF three- and five-factor models are estimated to describe returns on five M/B-ranked portfolios in Vietnam.

The US evidence of momentum is documented by Jegadeesh and Titman (1993). A trading behavior, which selects firms based on their returns over the past six months and holds them in the next six months, delivers an annual average return of about 12% between 1965 and 1989. Later on, Carhart (1997) creates the momentum factor by taking the return differential between winners and losers. The winner (loser) portfolio comprises stocks with the highest (lowest) previous 11-month returns. Then the Carhart four-factor model is developed by augmenting the FF three-factor model with the momentum factor. Examining returns on 27 quantitatively-managed portfolios, Carhart (1997) points out that his model well explains the variability in stock returns with a substantially lower pricing error than the CAPM and three-factor model. Fama and French (2012) declare that the Carhart model's performance is similar or better than the CAPM and FF three-factor model in capturing returns on 25 Size-M/B portfolios in 23 developed countries. Meanwhile, investigating 18 emerging markets during 1990-2011, Cakici et al. (2013) state that adding momentum only slightly enhances the three-factor model' power. Performances of both models are virtually equal for the size and M/B cross-section. To the best of our understanding, although there is empirical proof of the momentum effect in Vietnam (Vo and Truong, 2018), there is no published paper using momentum as an explanatory factor to Vietnamese stock returns. Therefore, this paper investigates whether momentum is a relevant factor in Vietnam.

4.3. Data

The 2009-2019 period is chosen because of two main reasons. Firstly, the number of shares and market capitalization before 2009 is relatively small. More importantly, when many large companies become listed in 2009, the stock market represents the Vietnamese economy (Quach et al., 2019). Secondly, there could be a great amount of noise in data before 2009 due to a stock market bubble during 2005-2007 and the financial crisis in 2008. After the second half of 2009, the

Vietnamese stock market has been gradually stabilizing thanks to the economic recovery.

The data sample includes all non-financial shares in the Ho Chi Minh exchange. As mentioned in chapter 3, financial stocks are excluded in most papers applying Fama-French models. Stock prices, which are adjusted closing prices, are obtained from DataStream. The weekly data interval is selected due to two reasons. Firstly, only prices at the beginning and the end of a month are considered for computing monthly returns, ignoring all other prices. However, in an emerging stock market such as Vietnam, the price may fluctuate considerably during a month. Therefore, the fluctuation in prices would be tracked more thoroughly when the weekly data interval is used. Furthermore, in Vietnam, as stocks are only tradable in three days after the transaction date, investors cannot earn the daily return in reality. Using daily data might also lead to non-trading bias because some small and value stocks are not traded on a daily basis. According to Damodaran (2012), when stock returns are calculated, the non-trading bias may arise because returns in non-trading periods are zero, although the market may move up or down significantly in those periods. Secondly, because of a short history of the Vietnamese stock market, there are only 120 monthly observations. Additionally, estimating multifactor models with monthly data leads to a high autocorrelation in residuals, then coefficients could be inefficient[2]. To reduce the impact of non-trading bias, stocks that are not traded in more than ten continuous business days would be omitted from the sample during that period. Moreover, to eliminate noises, stocks with weekly absolute returns of more than 35% are also removed.

Accounting data is gathered from a combination of DataStream and Fiingroup. Since there are several missing observations in accounting data of DataStream, the second source of data is Fiingroup, a leading financial data provider in Vietnam. Then, two databases are compared and matched. Overall, accounting data from both databases are identical. However, there are slight differences in the accounting figures of some small companies. Most of them are initially published, then their

[2] Durbin-Watson statistics for the monthly data interval are around 2.4, while Durbin-Watson statistics for the weekly data interval are close to 2

financial reports may not be standardized. Therefore, these firms are excluded from the sample. For missing observations in DataStream, accounting data is only collected from Finngroup if an independent audit company audits it. Otherwise, it is omitted from the sample.

Year	Number of stocks	Year	Number of stocks
2009	124	2015	265
2010	187	2016	279
2011	216	2017	304
2012	238	2018	319
2013	248	2019	340
2014	250		

Figure 5 - Total number of shares entering all portfolios, by year

The yield on the one-year Vietnamese government bond is regarded as the riskless rate. The VN-Index is considered as the market portfolio. They are also collected from DataStream.

4.4. Methodology

4.4.1. The construction of portfolios

Firstly, the M/B ratio is chosen as the criterion to categorize stocks. Fama and French (2007) point out that value portfolios based on the M/B provide more consistent and considerably higher returns than portfolios sorted by other multiples. Book value represents the accountant's valuation of the company's net worth, which is more stable than earnings over time. Furthermore, since being very sensitive to the firm's capital structure, the P/E should not be used to compare among firms with different leverages. Additionally, due to negative incomes, various firms may have negative P/E ratios, which are subject to be meaningless.

The second step is to rank stocks on the M/B ratio. Most of the previous studies sort stocks on an annual basis (Basu, 1977; FF, 1993, 1996, 2004, 2012, 2015, 2017; Jaffe et al., 2020). However, ranking stocks on a semiannual basis is likely to be more reasonable for Vietnam, since Vietnamese firms change their characteristic groups faster than firms in developed markets (as shown in appendix A1). Furthermore, many Vietnamese investors search for relatively short-run returns instead of buying and holding stocks for a long horizon (Quach et al., 2019). Therefore, the M/B ratio is calculated twice a year, in June and December.

To ensure that investors can obtain accounting data prior to portfolio formation, the firm's M/B ratio equals its market capitalization in June (or December) divided by its book equity in the previous fiscal year. The market capitalization of each firm is estimated by multiplying the number of outstanding shares with the stock price at the end of June (or December). It is undeniable that the estimation of the M/B ratio would be more proper using capitalization and book equity at the same time. However, in reality, based on available information, Vietnamese investors have to make decisions. Although listed firms must release their financial statements quarterly according to the regulation, many only publish their reports once a year in March or April. Furthermore, in Vietnam, quarterly reports are often not audited and are manipulated. Hence, the best way to calculate the M/B ratio is to use book equity in the previous fiscal year.

Stocks are divided into five M/B quintile portfolios. Each quintile portfolio could be viewed as an investment strategy for purchasing shares with a certain M/B group in June (December) and holding them for the next six months. At the beginning of January (July), proceeds from disposition are put into a similar M/B group. An important assumption underlying this technique is that investors purchase stocks in the beginning of January (or July) and hold them for the next six months. Their position is not changed during six months, which means that investors do not pay attention to movements in stock prices or any relevant news.

Then the value-weighted returns on five portfolios are computed. There are 515 weekly observations from July 2009 to June 2019.

Among five portfolios sorted on the M/B ratio, the growth quintile has the highest mean, at approximately 0.22% per week or 12% per year. The third portfolio has the lowest mean, which is close to zero. The standard deviation increases monotonically from growth to value quintiles. Investing in the growth leads to the highest profit with the lowest variance. Notably, standard deviations of all formed portfolios are extremely high in comparison to their means, which implies a significant fluctuation in stock prices. Because Jarque-Bera statistics are very high, it could be concluded that all returns are not normally distributed.

	1-Growth	2	3	4	5-Value
Mean (%)	0.225	0.190	0.014	0.056	0.134
Median (%)	0.305	0.186	0.107	0.130	0.065
Maximum (%)	15.334	12.233	14.185	11.372	15.181
Minimum (%)	-10.865	-11.605	-15.250	-14.561	-14.423
Std. Dev. (%)	2.870	2.974	3.060	3.486	3.894
Skewness	-0.051	0.007	-0.309	-0.233	-0.062
Kurtosis	5.791	4.927	7.057	4.818	4.582
Jarque-Bera	167.36	79.652	361.39	75.554	54.021
Probability	0.000	0.000	0.000	0.000	0.000
Observations	515	515	515	515	515

Figure 6 - Descriptions of weekly returns on five M/B-ranked portfolios

4.4.2. The CAPM and Fama-French multifactor models

To capture the returns of five M/B-ranked portfolios, the CAPM and FF multifactor models are estimated. The CAPM:

$$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + \varepsilon_{it}$$

Three-factor model:

$$R_{it} - R_{ft} = a_i + b_i * [\, R_{mt} - R_{ft}\,] + s_i * SMB_t + h_i * HML_t + \varepsilon_{it}$$

Five-factor model:

$$R_{it} - R_{ft} = a_i + b_i * [\, R_{mt} - R_{ft}] + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \varepsilon_{it}$$

R_{it} is the return of the portfolio i for period t. R_{mt} is the market return, and R_{ft} is the risk-free return. ε_{it} is the residual for period t.

As suggested by Fama and French (2016), four mimic factors are constructed as follows. The $SMB_{M/B}$ and HML (High Minus Low) are computed based on six Size-M/B portfolios. Firstly, based on their capitalization in June (or December), stocks are classified into large and small categories. Subsequently, 30% of firms with the highest (lowest) M/B ratios are grouped to growth (value) subcategories, and remaining stocks are placed into neutral subcategories. Then:

$$SMB_{M/B} = 1/3 \ * \ (\text{Small-Growth} + \text{Small-Neutral} + \text{Small-Value}$$
$$-\text{Big-Growth} - \text{Big-Neutral} - \text{Big-Value})$$

$$HML = 1/2 \ * \ (\text{Big-Value} + \text{Small-Value} - \text{Big-Growth} - \text{Small-Growth})$$

Similarly, the RMW (Robust Minus Weak) is constructed from six portfolios ranked on size and operating profit margin. The operating profit margin is the operating profit divided by book equity. The operating profit equals revenue minus the cost of goods sold, minus selling, general, and administrative expenses, minus interest expenses (Fama and French, 2016). Stocks with the highest operating profit margins are assigned to robust subgroups, whereas stocks with the lowest margins are put into weak subgroups.

$$RMW = 1/2 \ * \ (\text{Small-Robust} + \text{Big-Robust} - \text{Small-Weak} - \text{Big-Weak})$$

$$SMB_{OP} = 1/3 \ * \ (\text{Small-Robust} + \text{Small-Neutral} + \text{Small-Weak}$$
$$-\text{Big-Robust} - \text{Big-Neutrali} - \text{Big-Weak})$$

The CMA (Conservative Minus Aggressive) formation is identical to the RMW, but stocks are sorted on the increase in total assets. The lower the total assets' change, the much conservative a stock is (Fama and French, 2016). Therefore, firms with the lowest total assets are placed into conservative subgroups and firms with the highest increases in assets are categorized into aggressive subgroups.

$$CMA = 1/2 \ * \ (\text{Small-Conservative} + \text{Big-Conservative}$$
$$-\text{Small-Aggressive} - \text{Big-Aggressive})$$

$$SMB_{Inv} = 1/3 \ * \ (\text{Small-Conservative} + \text{Small-Neutral} + \text{Small-Aggressive}$$
$$-\text{Big-Conservative} - \text{Big-Neutral} - \text{Big-Aggressive})$$

Finally, the SMB (Small Minus Big) factor is:

$$SMB = 1/3 \ * \ (SMB_{M/B} + SMB_{OP} + SMB_{Inv})$$

To be consistent with the formation of five M/B portfolios, four mimic factors are rebalanced every six months.

4.4.3. The momentum factor

Since the momentum factor of Carhart (1997) is created from only two portfolios ranked on the past return, the size effect is not controlled. Following Fama and French (2012), the momentum factor is created from four portfolios sorted on size and the past return. Firstly, stocks are assigned to large and small groups based on their capitalization. In each group, 30% of shares with the highest (lowest) prior returns are labeled as winners (losers). These portfolios are also rebalanced twice a year. Then, the momentum factor (WML - Winner Minus Loser) is:

$$\text{WML} = 1/2 * (\text{Big-Winner} + \text{Small-Winner} - \text{Big-Loser} - \text{Small-Loser})$$

There are two methods of building the momentum factor. In the first approach of Jegadeesh and Titman (1993), for period t, the past returns are computed during the last six months. In the second, as suggested by Carhart (1997), Fama and French (2012), the past returns are estimated in the previous eleven months. As shown in Figure 7, the WML based on the last six-month period generates a higher average return, at 6.93% per year. It is consistent with Vo and Truong (2018) finding, who discover that strategies with a longer pre-formation period provide lower profitability in Vietnam. Therefore, in this research, both the pre-formation and holding periods of the WML factor are six months.

Pre-formation period	Big-Winner	Small-Winner	Big-Loser	Small-Loser	WML
6 months	16.823%	13.671%	7.468%	8.09%	6.93%
11 months	16.443%	13.147%	7.434%	9.308%	5.93%

Note: All stocks are assigned into four sub-portfolios based on their capitalization and past returns. Figure 7 displays the annual average returns of these sub-portfolios.

Figure 7 - Average returns of winner and loser with different pre-formation periods

	R_m - R_f	SMB	HML	RMW	CMA	WML
Mean (%)	0.075	0.085	-0.048	0.041	0.008	0.128
Median (%)	0.247	0.045	-0.074	0.000	0.028	0.150
Maximum (%)	11.515	5.148	8.575	6.863	4.763	4.324
Minimum (%)	-11.884	-5.889	-8.452	-6.971	-5.632	-5.488
STD (%)	2.822	1.533	2.146	1.957	1.427	1.459
Skewness	-0.377	-0.079	0.186	0.005	-0.171	-0.269
Kurtosis	4.917	3.459	4.446	3.585	4.008	4.425
Jarque-Bera	91.065	5.052	47.839	7.344	24.313	49.797
Probability	0.000	0.080	0.000	0.025	0.000	0.000
Observations	515	515	515	515	515	515

Note: The figure presents the descriptive statistics of time-serries returns on explanatory factors. The construction of six factors are given in section 4.4.2 and 4.4.3. STD stands for the standard deviation of returns. Probability is the p-value of the Jarque-Bera test with the null hypothesis that returns are normally distributed.

Figure 8 - Descriptions of weekly returns on explanatory factors

	R_m - R_f	SMB	HML	RMW	CMA	WML
R_m - R_f	1.000	-	-	-	-	-
SMB	-0.504	1.000	-	-	-	-
HML	0.159	0.224	1.000	-	-	-
RMW	-0.231	-0.158	-0.708	1.000	-	-
CMA	-0.162	0.224	0.268	-0.101	1.000	-
WML	0.056	-0.271	-0.680	0.373	-0.263	1.000

Figure 9 - Correlations among explanatory factors

The highest mean belongs to the WML factor, at approximately 0.13% per week. The WML factor provides the highest average return with the second-lowest standard deviation. Hence, it is subject to be a stable factor that earns a significant return. By contrast, the mean of CMA is nearly zero, at roughly 0.008%, which is equivalent to an annual return of only 0.41%. The concepts of aggressive and conservative stocks are relatively unfamiliar in Vietnam. Most Vietnamese securities firms and investors focus on the P/E, the dividend, cash flow, and profitability of stocks rather than their increase in total assets. Therefore, the number of institutional and individual investors who have strong investment tilts is very limited. As a result, the investment factor (CMA) provides a very low profit. Except for the SMB, as Jarque-Bera statistics are fairly high, returns on all explanatory factors are not normally distributed. Only returns on the SMB factor have a normal distribution at the significance of 5%. The highest absolute correlation between two explanatory variables is roughly 0.7, which raises no concern about multicollinearity.

4.5. Results and Discussions

4.5.1. The growth effect in the Vietnamese stock market

Notably, growth stocks outperform other stocks. During 2009-2019, investing in the growth portfolio leads to the highest average return, at more than 12.4% per year. By contrast, the annual average return on value portfolio is substantially lower, at only 7.2%. In the first sub-period from 2009 to 2014, the annual return differential between growth and value portfolios is about 8.26%. In the second sub-period between 2014 and 2019, growth and value portfolios generate average returns of 7.1% and 4.6% per year, respectively. In 7 out of 10 sample years, growth stocks outperform value stocks. Therefore, there is solid proof of a growth effect in Vietnam, contrary to the value effect in developed markets. Many studies in developed markets document a negative relationship between the M/B and average return (Fama and French, 1993, 1996, 2007a, 2012, 2016, 2017; Jaffe et al., 2020). In Vietnam, since growth stocks deliver superior returns compared to value stocks, the HML factor's return is negative, as shown in Figure 8. More interestingly, there would be approximately no return for an investor placing his fund in the neutral or third portfolios.

	1-Growth	2	3	4	5-Value
Annual average return (%)	12.415	10.374	0.731	2.943	7.206
Capitalization ($ million)	544.027	93.051	50.642	34.100	19.370
M/B	3.934	1.682	1.165	0.800	0.472
Operating profit margin (%)	25.623	19.311	15.087	9.471	3.704
Increase in assets (%)	39.405	22.646	20.904	16.494	9.410

Note: All sample stocks are divided into five M/B-ranked portfolios. The annual average return, the average values of market capitalization, market-to-book ratio, increase in total assets, and operating profit margins are reported in Figure 10.

Figure 10 - Analysis of five M/B-ranked portfolios

Growth stocks have considerably higher capitalization in comparison with value stocks. To illustrate, the growth has the highest mean capitalization during the sample period, at over $500 million, which is approximately 25 times the mean capitalization of the value ($19.37 million). The average M/B ratio of growth portfolio is extremely high, at 3.934. On average, Vietnamese investors are willing to pay nearly four times their book values to purchase growth stocks. The mean M/B for the next three portfolios is close to 1, which implies that their intrinsic values are likely to be equivalent to their market values. Value stocks appear to be modestly priced, with an average M/B of only 0.472.

From 2009 to 2019, growth stocks are the most profitable stocks with an average operating margin of roughly 25%, while value stocks are subject to perform inferiorly with relatively low operating margin, at only 3.7%. Growth stocks are also the most aggressive stocks. On average, they raise their total assets by about 40% per year. Meanwhile, the most conservative stocks are value stocks, with a yearly increase in total assets of 9.4%. It is consistent with Fama and French (2016); growth stocks tend to sustain high profits and invest aggressively, while value stocks' profits and investment tend to be below-average.

4.5.2. Results of the CAPM and Fama-French multifactor models

Although the b coefficient is significant with very high t-statistics in all regressions, the CAPM cannot explain the superior returns on growth stocks. While the growth quintile provides a substantially higher return than the value quintile (see Panel A of Figure 11), estimated betas for both portfolios are nearly the same, at roughly 0.95.

Compared to the CAPM, the FF three-factor model is better with regard to explaining portfolio returns. The average adjusted R^2 for CAPM regressions is 0.656, whereas the average adjusted R^2 for three-factor regressions is about 0.8. Moreover, the average absolute values of alpha in CAPM and three-factor regressions are around 8 and 7.4 basis points, respectively. Since Durbin-Watson statistics are close to 2, there is little evidence of autocorrelation. Thus, adding the SMB and HML factors into the CAPM leads to a considerable improvement in the explanatory power.

At the level of 0.05, the s coefficient is significant in four regressions, and the h coefficient is significant in all regressions. As growth firms have higher capitalization than value firms, the slope of the SMB factor rises from growth to value portfolios. As expected, the coefficient of the HML factor also increases monotonically between growth and value quintiles. However, slopes of SMB and HML cannot completely explain returns on growth and value shares. According to the results of Panel B in Figure 11, equations for expected returns are:

$$E\left(R_{growth}\right) = R_f + 0.928E(R_m - R_f) - 0.152E(SMB) - 0.22E(HML)$$

$$E(R_{value}) = R_f + 0.951E(R_m - R_f) + 0.333E(SMB) + 0.985E(HML)$$

$$E\left(R_{growth} - R_{value}\right) = -0.023E(R_m - R_f) - 0.485E(SMB) - 1.205E(HML)$$

Based on weekly average returns of explanatory factors in Figure 6, we have:

$$E\left(R_{growth} - R_{value}\right) = -0.023 * 0.075 - 0.485 * 0.085 + 1.205 * 0.048 = 0.015\%$$

Panel A: Results of the CAPM				
$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + \varepsilon_{it}$				
	a(%)	b	Adj. R^2	DW
1-Growth	0.044 (-0.926)	0.943*** (38.827)	0.86	2.179
2	0.014 (0.187)	0.873*** (28.864)	0.685	1.977
3	-0.162** (-2.003)	0.869*** (20.261)	0.641	1.993
4	-0.126 (-1.292)	0.951*** (21.552)	0.592	1.938
5-Value	-0.05 (-0.417)	0.979*** (19.161)	0.502	1.704

Panel B: Results of the FF three-factor model						
$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + s_i * SMB_t + h_i * HML_t + \varepsilon_{it}$						
	a(%)	b	s	h	Adj. R^2	DW
1-Growth	0.047 (1.17)	0.928*** (42.025)	-0.152*** (-4.049)	-0.22*** (-9.663)	0.899	2.125
2	0.054 (0.809)	0.778*** (23.712)	-0.177*** (-2.853)	0.386*** (10.181)	0.751	1.972
3	-0.145** (-2.366)	0.839*** (21.663)	0.129** (2.086)	0.542*** (15.926)	0.799	1.998
4	-0.094 (-1.378)	0.886*** (24.207)	0.091 (1.444)	0.742*** (18.542)	0.807	1.958
5-Value	-0.029 (-0.428)	0.951*** (27.9)	0.333*** (5.348)	0.985*** (27.019)	0.845	1.907

Panel C: Results of the FF five-factor model								
$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + s_i * SMB_t + h_i * HML_t + r_i * RMW_t + c_i * CMA_t + \varepsilon_{it}$								
	a(%)	b	s	h	r	c	Adj. R^2	DW
1-Growth	0.045 (1.129)	0.936*** (40.785)	-0.138*** (-3.628)	-0.161*** (-4.049)	0.087** (2.046)	-0.034 (-1.176)	0.901	2.109
2	0.05 (0.76)	0.795*** (23.67)	-0.176*** (-2.94)	0.405*** (6.374)	0.063 (0.912)	0.108* (1.95)	0.754	1.971
3	-0.148** (-2.455)	0.856*** (22.084)	0.118* (1.92)	0.519*** (11.582)	0.014 (0.293)	0.174*** (3.771)	0.804	2.000
4	-0.099 (-1.46)	0.907*** (24.499)	0.089 (1.413)	0.759*** (13.276)	0.07 (1.193)	0.140** (2.482)	0.81	1.946
5-Value	-0.03 (-0.443)	0.956*** (27.497)	0.328*** (5.342)	0.971*** (17.474)	-0.004 (-0.065)	0.062 (1.136)	0.845	1.913

Note: Because of the heteroscedasticity, robust standard errors are estimated following White (1980). t-statistics are in parentheses. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 11 - Results of the CAPM and FF multifactor models

The expected difference between returns on growth and value quintiles is only 0.015% per week or 0.78% per year. However, the actual difference is more than 5% per annum (see Figure 10). Therefore, the FF three-factor model cannot fully describe the returns of growth and value stocks.

Statistically, the RMW and CMA factors are likely to be insignificant explanatory variables to stock returns. As shown in Panel C, at the 5% level, the RMW factor is significant in only one regression, and the CMA factor is significant in only two out of five regressions. It is in line with Leite et al. (2018), who find little evidence of profitability effects and only some investment effects in twelve emerging markets between 2007 and 2017. Although appropriately explaining stock returns in developed markets, the FF five-factor model performs poorly in Vietnam.

According to Barillas and Shanken (2017), if other factors capture the average return on an explanatory factor in an asset pricing model, this factor would include no additional information. Hence, each factor is regressed on the others. If the regression alpha of a factor is insignificant, this factor should not be added to the model. As displayed in Figure 12, intercepts of HML, RMW, and CMA factors are indistinguishable from zero at both significance levels of 10% and 5%. Consequently, they add no incremental information and should be excluded from the asset pricing model.

	Intercept (%)	R_m - R_f	SMB	HML	RMW	CMA	Adj. R^2	DW
R_m-R_f	0.186^{*}	-	-1.013^{***}	0.202^{***}	-0.317^{***}	-0.203^{***}	0.364	1.944
	(1.856)	-	(-13.17)	(2.934)	(-4.317)	(-2.688)		
SMB	0.118^{**}	-0.302^{***}	-	0.138^{***}	-0.112^{***}	0.072^{*}	0.356	1.825
	(2.15)	(-10.29)	-	(3.575)	(-2.704)	(1.656)		
HML	-0.044	0.083^{***}	0.189^{***}	-	-0.704^{***}	0.286^{***}	0.549	1.953
	(-0.676)	(2.766)	(3.631)	-	(-15.48)	(4.896)		
RMW	0.03	-0.114^{***}	-0.136^{**}	-0.619^{***}	-	0.107^{*}	0.524	1.943
	(0.504)	(-3.964)	(-2.572)	(-16.10)	-	(1.949)		
CMA	0.014	-0.072^{**}	0.086^{*}	0.247^{***}	0.105^{**}	-	0.122	1.847
	(0.238)	(-2.418)	(1.688)	(5.718)	(2.09)	-		

Note: Because of the heteroscedasticity, robust standard errors are estimated following White (1980). t-statistics are in parentheses. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 12 - Results of redundancy tests for five factors

To sum up, the CAPM and FF multifactor models cannot completely capture returns on five M/B-ranked portfolios in the Vietnamese stock market. Three out of four mimic factors (HML, RMW, and CMA) contain no incremental information on expected returns relative to the market premium and SMB factor. Therefore, the explanatory power of FF models to Vietnamese stock returns seems to be limited.

4.5.3. Momentum explains the growth effect

4.5.3.1. Momentum contains incremental information

To gauge the additional information that the momentum factor contains on expected returns in comparison to the CAPM and FF models, spanning regressions are estimated with the WML being the dependent variable. According to the results of Figure 13, the momentum factor includes information incremental to the CAPM and FF models. In three regressions, WML alphas are always significantly positive, at around 10 basis points with t-statistics of approximately 2. In other words, investors who trade the market and FF mimic factors still could benefit from the information included in the momentum factor. Hence, it is difficult to capture the momentum return with a risk-based model, which motivates us to examine other explanations in the following section.

	Intercept (%)	$R_m - R_f$	SMB	HML	RMW	CMA	Adj. R^2	DW
WML	0.127**	0.029	-	-	-	-	0.001	1.968
	(1.967)	(0.971)	-	-	-	-		
WML	0.104**	0.075***	-0.04	-0.471***	-	-	0.49	2.092
	(2.216)	(3.222)	(-0.967)	(-16.63)	-	-		
WML	0.109**	0.054**	-0.056	-0.548***	-0.139***	-0.037	0.51	2.115
	(2.372)	(2.405)	(-1.384)	(-16.11)	(-3.799)	(-1.030)		

Note: Because of the heteroscedasticity, robust standard errors are estimated following White (1980). t-statistics are in parentheses. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 13 - Results of spanning regressions

4.5.3.2. The momentum return after portfolio formation

By tracking the momentum return after portfolio construction, we investigate three main hypotheses explaining the momentum effect (see section 2.3.2). Firstly, if investors underreact to new information when updating their priors, stock prices would gradually adjust to information (Jegadeesh and Titman, 2001). Once prices fully reflect new information, the returns on winners and losers would be nearly the same. Consequently, the WML would generate positive returns in a short period following portfolio construction but zero returns over the long run. Secondly, if investors overreact to information about the prior return, prices of winners (losers) would be pushed above (below) their intrinsic values (Daniel et al., 1998). Over the long term, stock prices should be adjusted toward fundamental values. Therefore, the WML factor's return would be highly positive in initial periods after portfolio formation and negative in the long run. The third explanation is declared by Conrad and Kaul (1998). They suggest that stock prices follow a random walk with unconditional drifts that varies across stocks. Hence, winners earn higher returns than losers, thanks to higher unconditional drifts. As a result, over the long term, winners still outperform losers, which leads to a positive return on the WML.

To evaluate three different explanations, the returns on winner and loser following portfolio construction are tracked. Although Jegadeesh and Titman (1993, 2001) investigate the momentum return in 36 and 60 months, due to a short history of the Vietnamese market, the WML factor's return is examined up to 24 months.

	Months 1-3	Months 4-6	Months 7-9	Months 10-12
Big-Winner	2.703%***	-0.164%	1.708%*	-0.665%
	(12.155)	(-0.154)	(2.819)	(-0.721)
Small-Winner	1.971%*	0.147%	1.46%**	-0.19%
	(3.081)	(0.189)	(3.554)	(-0.512)
Big-Loser	2.116%**	-0.869%	1.528%**	-0.354%
	(5.631)	(-0.965)	(4.518)	(-0.627)
Small-Loser	1.429%	-0.088%	0.773%	0.141%
	(1.516)	(-0.161)	(0.827)	(0.324)
WML	0.517%	0.516%*	0.473%	-0.45%
	(1.203)	(3.106)	(0.67)	(-2.046)
	Months 13-15	Months 16-18	Months 19-21	Months 22-24
Big-Winner	1.127%*	-1.968%***	1.53%	-1.567%**
	(2.356)	(-7.152)	(3.153)	(-3.297)
Small-Winner	0.743%	-0.015%	1.37%**	-0.468%
	(0.947)	(-0.046)	(4.784)	(-1.09)
Big-Loser	1.871%***	-0.725%	1.97%**	-0.159%
	(9.383)	(-1.434)	(3.943)	(-0.43)
Small-Loser	1.704%**	0.049%	2.146%***	0.614%*
	(3.465)	(0.301)	(8.678)	(2.842)
WML	-0.853%*	-0.653%**	-0.61%*	-1.245%**
	(-3.01)	(-4.791)	(-2.315)	(-3.81)

Note: For the sake of brevity, the average returns every three months are reported. t-statistics are in parentheses. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 14 - Returns of winner and loser after portfolio formation

The WML factor provides positive profitability in only 9 months after portfolio formation, with a monthly average return of around 0.5%. From month 10 to month 24, losers outperform winners, which leads to negative returns on the WML. This result is in line with Vo and Truong (2018), who discovers that the WML return decreases substantially when the holding period rises from 9 to 12 months. Over the second year following portfolio construction, the WML's monthly average return is roughly -0.84%. The momentum return is significantly negative in all 12 months with high t-statistics. It could be regarded as evidence supporting the second hypothesis. Because Vietnamese investors overreact to the past return information, prices of winners and losers are driven further from their fundamental values, which leads to the excess return of the momentum factor. After 9 months of delayed overreaction, stock prices are adjusted toward their intrinsic values. Then, the loser provides considerably higher returns than the winner. As a result, the delayed overreaction is likely to be the key reason behind Vietnam's momentum effect.

4.5.3.3. Momentum explains the growth effect

Since the HML, CMA, and RMW do not include additional information as previously discussed, a three-factor model with the market, WML, and SMB factors are examined in this section. Statistically, regressions with the momentum factor give a relatively good description of the variability of portfolio returns. The average adjusted R^2 is relatively high, at 0.8, and the average absolute alpha is only about 5.5 basis points. Durbin-Watson statistics are approximately 2, which implies no autocorrelation. The market premium, SMB, and WML factors are significant at the 0.01 level in all regressions with fairly high t-statistics. The w coefficient decreases from growth to value quintiles, which indicates that growth stocks are likely to move together with winners, while value shares tend to be losers. It is in line with the characteristics of growth and value firms, as previously mentioned. Alphas of growth and value quintiles in the FF three-factor model are 4.7 and -2.9 basis points, respectively. Meanwhile, in the three-factor model with momentum, alphas of growth and value portfolios are approximately zero, at only 0.6 and 1.4 basis points, respectively.

More importantly, this model does an excellent job of capturing returns on growth and value portfolios. According to Figure 15, equations of expected returns are:

$$E\left(R_{\text{growth}}\right) = R_f + 0.89E(R_m - R_f) - 0.148E(\text{SMB}) + 0.418E(\text{WML})$$

$$E(R_{\text{value}}) = R_f + 1.168E(R_m - R_f) + 0.586E(\text{SMB}) - 0.997E(\text{WML})$$

$$E\left(R_{\text{growth}} - R_{\text{value}}\right) = -0.278E(R_m - R_f) - 0.734E(\text{SMB}) + 1.415E(\text{WML})$$

Based on weekly average returns on explanatory factors in Figure 8, we have:

$$E(R_{growth} - R_{value}) = -0.278 * 0.075 - 0.734 * 0.085 + 1.415 * 0.128 = 0.097\%$$

$$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + s_i * SMB_t + w_i * WML_t + \varepsilon_{it}$$

	a(%)	b	s	w	Adj. R^2	DW
1-Growth	0.006	0.89***	-0.148***	0.418***	0.918	2.083
	(0.169)	(44.82)	(-4.431)	(13.21)		
2	0.119*	0.847***	-0.17***	-0.69***	0.79	1.99
	(1.9)	(29.51)	(-3.172)	(-13.75)		
3	-0.097	0.95***	0.222***	-0.699***	0.778	2.086
	(-1.48)	(26.88)	(3.676)	(-14.03)		
4	-0.04	1.042***	0.24***	-0.884***	0.754	2.023
	(-0.509)	(26.85)	(3.66)	(-16.23)		
5-Value	0.014	1.168***	0.586***	-0.997***	0.722	1.984
	(0.153)	(27.42)	(7.304)	(-15.04)		

Note: Because of the heteroscedasticity, robust standard errors are estimated following White (1980). t-statistics are in parentheses. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 15 - Results of the three-factor model with momentum

The expected weekly differential between returns on growth and value portfolios is 0.097%, which is equivalent to an annual return differential of 6.5%. It is accordant with the average returns displayed in section 4.5.1. The growth portfolio yields a 5.2% annual higher return than the value. Hence, a model, including the market premium, SMB, and WML factors completely explains Vietnam's growth effect. Due to high exposure to the WML factor, the momentum effect is the main reason for excess returns on growth stocks. Meanwhile, the momentum effect arises from the delayed overreaction. As shown in Figure 10, most growth firms are big companies with high-profit margins, which are preferred by numerous Vietnamese investors (Vo and Bui, 2016). Furthermore, in Vietnam, investors tend to follow collective behavior (Vo and Phan, 2017). Consequently, growth stocks' prices are pushed above their long-run values due to the delayed overreaction to the good news about their prior returns[3]. As a consequence, investing in the growth portfolio delivers a superior return.

There are two robustness tests for the three-factor model with momentum. They are the redundancy test (Barillas and Shanken, 2017) and the GRS test (Gibbons et al., 1989).

	Intercept (%)	R_m-R_f	SMB	WML	Adj. R^2	DW
R_m-R_f	0.180*	-	-0.97***	-0.168*	0.258	1.84
	(1.69)	-	(-11.61)	(-1.86)		
SMB	0.138**	-0.266***	-	-0.256***	0.31	1.776
	(2.435)	(-9.66)	-	(-5.84)		
WML	0.159**	-0.056*	-0.31***	-	0.078	2.05
	(2.553)	(-1.924)	(-5.99)	-		

Note: Because of the heteroscedasticity, robust standard errors are estimated following White (1980). t-statistics are in parentheses. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 16 - Redundancy tests for the market, size, and momentum factors

Intercepts of the SMB and WML factors are statistically positive with high t-statistics, at 2.435 and 2.553, respectively. At the level of 10%, the intercept of the market factor is also significantly positive, with a t-statistic of about 1.7. Therefore, all three factors contain incremental information on expected returns.

The GRS test is used to investigate whether five regression alphas of portfolios simultaneously equal to zero. The GRS test-statistic:

$$\text{GRS statistic} = \frac{\mathrm{T(T-N-L)}}{\mathrm{N(T-L-1)}} * \frac{\hat{a}'\hat{\varepsilon}^{-1}\hat{a}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}} \sim \mathrm{F(N, T-N-L)}$$

T and L are the numbers of observations and explanatory factors (thus T=515 and L=3). N is the number of tested portfolios (thus N=5). $\hat{a}$ is a 5 by 1 column vector of alphas and $\bar{\mu}$ is a 3 by 1 column vector of sample means for factors' returns. $\hat{\varepsilon}$ is the residual covariance matrix. $\hat{\Omega}$ is the factors' covariance matrix.

[3] The growth quintile only outperforms the value in the first 9 months after portfolio formation (see Appendix A2)

The GRS test-statistic is 1.877, which is less than the critical value of 2.21. Hence, at the level of 5%, it could be concluded that regression alphas of five formed portfolios jointly equal zero. In other words, the market premium, SMB, and WML factors fully explain portfolio returns.

Taken together, a model with the market, size, and momentum factors does a great job in capturing returns on growth and value stocks. Momentum includes incremental information on expected returns and is a significant explanatory factor to portfolio returns.

4.6. Conclusion

As the value effect is discovered in numerous markets, the term "value and growth" becomes a well-known label in the financial lexicon. However, in the Vietnamese stock market, growth stocks outperform value stocks. From 2009 to 2019, the average return on growth portfolio is more than 12.4% per year, while the yearly average return on value portfolio is considerably lower, at only 7.2%. There is evidence of a growth effect, as reported by Quach et al. (2019).

The CAPM, Fama-French three- and five-factor models cannot explain expected returns on growth and value stocks. The value factor has a negative return, while profitability and investment factors seem to be insignificant explanatory variables. Among four mimic factors, only the size factor has a significant intercept in the redundancy test. The others are redundant factors.

Since there is proof of the momentum effect in Vietnam (Vo and Truong, 2018), we use the momentum factor as an explanatory variable to stock returns. Firstly, to investigate whether the momentum factor contains incremental information, it is regressed on the market premium and Fama-French mimic factors. Significantly positive alphas imply that momentum contains additional information and should be included in the asset pricing model. Secondly, three alternative explanations of the momentum effect are examined by tracking the momentum return following portfolio formation. In the second year, the momentum factor generates a significantly negative average return, which indicates that the momentum effect's main source is the delayed overreaction of Daniel et al. (1998). Finally, the empirical result shows that a three-factor model with momentum gives an appropriate explanation of returns on growth and value portfolios. Because of high exposure to the momentum factor, the growth portfolio's superior return arises from the momentum effect. Most growth stocks are issued by big and highly profitable firms, which represent attractive investments. Hence, due to the presence of herd behavior, investors are inclined to overreact to the good news about their past stock returns, sending their stock prices to unduly high levels. It is the key reason why the growth portfolio outperforms other portfolios. Both the redundancy test and the GRS test demonstrate the explanatory power of the three-factor model with momentum.

In conclusion, in Vietnam, the momentum factor includes incremental information on expected returns relative to the Fama-French models and is a significant explanatory factor to portfolio returns. Furthermore, momentum plays an essential role in explaining the Vietnamese market's growth effect, which is accordant with a behavioral point of view.

5. Momentum and overreaction in the Vietnamese stock market

Although the solid empirical proof of momentum is documented in various stock markets, there are a great number of debates among academics with respect to the source of momentum profit. This chapter contributes to the extant literature in three key aspects. Firstly, evidence of momentum is documented in the Vietnamese stock market during 2009-2019, consistent with Vo and Truong (2018). Secondly, the model of Daniel et al. (1998) is considered as one of the leading behavioral explanations of momentum. Hence, motivated by their model, we propose a measure of overreaction in Vietnam based on trading volume and the sign of stock returns. This measure of overreaction seems to be a predictor of stock returns. Stocks that have experienced a stronger upward overreaction earn a higher average return. Finally, while the momentum profit disappears after controlling for the effect of overreaction, the trading strategy based on overreaction yields significant returns even after we adjust for the momentum effect. Keeping past returns constant, the average returns of portfolios increase monotonically with their measure of overreaction. By contrast, no linear negative relationship between portfolio returns and past returns is apparent within each overreaction quintile. Given this backdrop, momentum in Vietnam arises from the investors' overreaction to private information as suggested by Daniel et al. (1998).

5.1. Introduction

As initially documented by Jegadeesh and Titman (1993), a momentum strategy that is long shares with high past returns and short shares with low part returns would earn an abnormal return. Over the last decades, numerous studies provide solid evidence of the momentum profit in many different equity markets. Momentum is not only discovered in developed markets such as the US (Jegadeesh and Titman, 2001; Asness et al., 2013; Byun et al., 2016), Europe (Van Dijk and Huibers, 2002; Doukas and McKnight, 2005; Antoniou et al., 2007; Huhn and Scholz, 2019), but also in various emerging markets (Rouwenhorst, 1999; Cakici et al., 2013, Butt et al., 2021).

Although momentum is comprehensively investigated, the source of momentum profit is controversial. Grundy and Martin (2001) state that the momentum profitability is not compensation for bearing a higher risk level. From the behavioural explanation, momentum seems to arise from the investors' overreaction. Daniel et al. (1998) argue that many investors tend to overestimate their ability to obtain private information and forecast stock prices. They are defined as overconfident investors. Some of their predictions might be appropriate when public information signals arrive, which increases their level of confidence due to biased self-attribution. Consequently, overconfident investors continue overreacting to private information. Continuing overreaction leads to momentum in share prices over a short period. In the long term, stock prices would be adjusted to their fundamental values, which leads to the reversal. Later on, there are several studies providing supporting evidence of this explanation: Lee and Swaminathan (2000), Cooper et al. (2004), Hwang (2010), Byun et al. (2016), Hur and Singh (2016).

The momentum profit in the Vietnamese stock market is reported by Vo and Truong (2018). The most profitable momentum strategy is to choose equities based on past performance in the last six months and hold them for the next nine months. In chapter 4, we construct the momentum factor from four mimic portfolios sorted on size and the past six-month returns. Tracking the return up to 24 months, we find that the momentum factor only generates positive returns in the first nine months. After nine months of delayed overreaction, stocks prices are adjusted toward their intrinsic values, then the return of momentum factor is significantly negative. These results are consistent with the explanation of Daniel et al. (1998).

The key motivation of this chapter is twofold. Firstly, we intensively re-examine the momentum profit in Vietnam between 2009 and 2019 by analyzing more than 300 non-financial shares in the Ho Chi Minh exchange. Secondly, since the

Vietnamese stock market is established in only more than twenty years, many Vietnamese investors are less experienced and less rational. Less experienced investors tend to be more overconfident in their ability and trade more aggressively (Odean, 1998). Hence, motivated by Daniel et al. (1998) and Byun et al. (2016), we build a measure of investors' overreaction, which is based on trading volume and the sign of stock returns. A combination of high trading volume and positive returns indicates the overreaction to positive private information, which pushes stock prices above their intrinsic values. Conversely, a high trading volume associated with negative returns implies the overreaction to negative private information, forecasting a decrease in share prices. To the best of our knowledge, there has been no published paper investigating overreaction and stock returns in Vietnam.

This chapter makes three main contributions. In the first place, we discover the empirical evidence of momentum in the Vietnamese equity market, which is in line with Vo and Truong (2018). Secondly, our measure of overreaction could be a predictor of Vietnamese stock returns. Stocks that have experienced a stronger upward overreaction provide a higher average return. Finally, returns on trading strategies based on overreaction are robust after adjusting for momentum, while returns on momentum portfolios become insignificant after adjusting for overreaction. The overreaction strategy also yields higher risk-adjusted returns than momentum. By double-sorting, we document that holding past returns constant, the average returns of portfolios rise monotonically with their measure of overreaction. Meanwhile, there is no pattern in the average returns of portfolios sorted on past returns within each overreaction quintile. Hence, it could be concluded that the momentum profit in Vietnam arises from investors' overreaction.

5.2. Literature Review

One of the most well-known stock market anomalies is the relation between a stock's return and its previous performance, which is known as momentum. It suggests that shares with high past returns during a medium period would generate a high return subsequently, while stocks with low past returns would continue falling. High-performance and low-performance shares are regarded as winners and losers. The pioneering work is carried out by Jegadeesh and Titman (1993). Analyzing the US market between 1965 and 1989, they find that a long-short zero-cost portfolio based on the past six-months returns provides an average excess monthly return of 0.95% over the next six months. Later on, the momentum profitability in the US is confirmed by Asness (1997); Jegadeesh and Titman (2001); Asness et al. (2013); Byun et al. (2016). Momentum is also discovered in other European developed markets (Van Dijk and Huibers, 2002; Doukas and McKnight, 2005; Antoniou et al., 2007; Huhn and Scholz, 2019). Furthermore, the momentum effect is found in emerging equity markets in Asia, Latin America, Eastern Europe, and Africa (Rouwenhorst, 1999; Cakici et al., 2013; Hanauer and Linhart, 2015; Butt et al., 2021).

Despite the solid empirical evidence of momentum in many equity markets over different periods, numerous debates have sparked among researchers and academics with regard to the source of momentum profit. The risk-based point of view cannot give a reasonable explanation of the momentum profitability. The Fama-French three-factor model is unable to capture the momentum profitability in the US (Fama and French, 1996; Grundy and Martin, 2001). Yu (2012) shows that the momentum strategy generates significantly positive risk-adjusted returns within the framework of the Fama-French three-factor model and the Carhart four-factor model. Momentum is also not driven by industry risk (Grundy and Martin, 2001) or business cycle variables (Cooper et al., 2004). Conrald and Kaul (1998) declare that the momentum profit simply reflects cross-sectional variability in average returns. According to their hypothesis, winners should continue to outperform losers in any post ranking period. It is inconsistent with the empirical result of Jegadeesh and Titman (2001), who point out that losers earn a significantly higher average return than winners after one year of portfolio formation.

From the behavioral explanation, a large number of studies postulate that the overreaction of investors causes momentum. Daniel et al. (1998) declare that numerous investors have a tendency to overestimate their ability to obtain private information and underestimate their forecast errors. These investors are known as overconfident investors. Overconfidence means having mistaken valuations and believing in them too strongly. Some of their predictions might be appropriate when public information signals arrive, which increases their level of confidence due to biased self-attribution. Self-attribution bias is a cognitive process in which people give credit their own talents and abilities for past successes, while blaming their failures on bad luck. In other words, high past portfolio returns make investors overconfident due to a self-attribution bias. They feel overconfident in the sense that they believe themselves to be better investors than others in terms of investment management (Glaser and Weber, 2009). As a result, overconfident investors continue overreacting to private information. Continuing overreaction causes momentum in share prices in a short period. However, over the long term, securities prices would be adjusted to their fundamental values, which leads to long-term reversals. There is empirical evidence supporting Daniel at al. (1998). The positive relation between the momentum profitability and proxies of investor overconfidence is reported in several papers. Lee and Swaminathan (2000) state that past trading volume forecasts both the persistence and magnitude of momentum profit. According to Cooper et al. (2004), the average monthly momentum profit is significantly positive (negative) following positive (negative) market returns. Furthermore, Hwang (2010) finds that the momentum effect increases if the correlation of investors' forecast errors is higher, which is consistent with the prediction of Daniel et al. (1998). Using the signed trading volume to measure continuing overreaction (see details in section 5.3.2), Byun et al. (2016) point out that continuing overreaction is better than past returns in predicting future returns. A strategy, which is long shares with upward continuing overreaction and short shares with downward continuing overreaction, earns a considerably positive profit of 0.91% per month during 1965-2009. Using a new measure that directly captures the speed with which stocks react to firm-specific information, Hur and Singh (2016) assert that momentum profits are consistent with behavioral models' predictions regarding investors' overreaction.

In Vietnam, evidence of momentum is discovered by Vo and Truong (2018). Examining 197 shares in the Ho Chi Minh exchange from 2007 to 2015, they report that ten out of sixteen momentum strategies generate significantly positive returns.

A momentum strategy, which chooses shares based on the past six months and holds them for the next nine months, is the most profitable strategy. Additionally, momentum profitability persists after subtracting transaction costs. In the previous chapter, we build the momentum factor from four mimic portfolios sorted on size and the past six-month returns. Between 2009 and 2019, the annual average return of momentum factor is 6.88%. Furthermore, to evaluate three different explanations of momentum, we track the momentum return up to two years after portfolio formation. The momentum factor only earns positive returns during the first nine months after the formation, which is consistent with Vo and Truong (2018). From month 10 to month 24, losers outperform winners. This evidence provides support for the delayed overreaction of Daniel et al. (1998). Given this backdrop, the momentum effect exists in Vietnam and the key source behind this effect is likely to be the investors' overreaction.

5.3. Methodology

5.3.1. Data sample

Data sample is similar to Chapter 4. The stock data of non-financial companies listed on the Ho Chi Minh City stock exchange are obtained from DataStream database. Banks, insurance companies, and securities corporations are excluded due to their different nature of business. Our sample period covers July 2009 to June 2019. The research data should meet three criteria. (1): firms must be listed and remain listed during the period of investigation over 2009-2019. (2): the absolute value of weekly returns is always less than 35%. (3): any stock that is not traded in ten continuous days is removed. Figure 17 reports the coverage of the data sample.

Year	Number of stocks	Year	Number of stocks
2009	124	2015	265
2010	187	2016	279
2011	216	2017	304
2012	238	2018	319
2013	248	2019	340
2014	250		

Figure 17 - Coverage of the data sample

5.3.2. Overreaction measure

According to Daniel et al. (1998), due to biased self-attribution, investors become more overconfident, which leads to continuing overreaction. Following Byun et al. (2016), we build the overreaction measure as follows. Firstly, trading volume is used as a proxy for the degree of overreaction. Overconfident investors tend to trade excessively, increasing trading volume. The positive relationship between overconfidence and trading volume is documented in many papers. Odean (1998) argue that trading volume would rise substantially when price takers, insiders, or market makers are overconfident, which is considered as the most robust effect of overconfidence. Glaser and Webber (2007) ask about 3,000 online broker investors to answer a questionnaire which is designed to measure the level of overconfidence. Investors who think that they are above average in terms of investment skills or past performance tend to trade more. It is consistent with overconfidence stories based on biased self-attribution. Based on trading records from 1995 through 2002 of all household investors domiciled in Finland, Grinblatt and Keloharju (2009) state that overconfidence is significantly related to trading at the 5% level. In the case of logged number of trades, a unit increase in overconfidence generates almost a 4% increase in trades. Using a dataset on trades, prices, and information of US traded firms over 2001-2010, Kelley and Tetlock (2013) conclude that, without overconfidence-based trading, over 99% of trading volume disappears. Similarly, Daniel and Hirshleifer (2015) declare that overconfidence leads to the excessive trading of individual investors, even in the face of transactions costs. The results of simulation analyses show that a measure of continuing overreaction based on trading volume is a good proxy of that directly based on the level of overconfidence (Byun et al., 2016). A positive link between overconfidence and trading volume is also found in the Chinese and Indian stock markets between 2002 and 2016 (Gupta et al., 2018). Secondly, only using trading volume might be not enough to capture the direction of overreaction since both the winner and loser portfolios tend to experience high trading volume (Jeffrey et al., 2009). Hence, we assume that the direction of overreaction is identified by the sign of contemporaneous return. As a result, a combination of high trading volume and positive (negative) return implies overreaction to positive (negative) private information. The signed trading volume for stock i during week t (SV_{it}) is:

$$SV_{i,t} = \begin{cases} TV_{i,t} & \text{if } r_{i,t} > 0 \\ 0 & \text{if } r_{i,t} = 0 \\ -TV_{i,t} & \text{if } r_{i,t} < 0 \end{cases}$$

Where $TV_{i,t}$ is the weekly trading volume, which equals the sum of daily trading volume in each week. The daily trading volume of a stock is the product of its traded shares multiplied by its closing price. $r_{i,t}$ is the return of stock i during week t.

Finally, the level of overreaction, denoted by OR, is the sum of signed trading volume divided by the average trading volume over the past six months:

$$OR_{i,t} = \frac{SV_{i,t-1} + SV_{i,t-2} + \cdots + SV_{i,t-j}}{\text{average}(TV_{i,t-1} + TV_{i,t-2} + \cdots + TV_{i,t-j})}$$

Where $OR_{i,t}$ is the measure of overreaction for stock i at week t. j is the length of the formation period. Since the level of overreaction is estimated based on the last six months, j is usually equal to 24 or 25. According to Daniel et al. (1998), the main driver of the medium-term return predictability is biased self-attribution, which leads to continuing overreaction of overconfidence investors. Then, they have a tendency to trade excessively, which is characterized by continuous high trading volume associated with stock returns. By summing the signed trading volume and normalizing the sum by the average trading volume, we capture the level of overreaction. A highly positive OR indicates that investors overreact to positive returns of a stock during a period of time, which pushes its price above the intrinsic value. By contrast, a considerably negative OR implies delayed overreaction to negative stock returns, decreasing its price.

5.3.3. Portfolio formation

According to Vo and Truong (2018), in Vietnam, the pre-formation and post-formation periods of the most profitable momentum strategy are six months and nine months, respectively. As documented in chapter 4, a momentum factor based on the last six-month period generates a higher average return than a momentum factor based on the past eleven months. The return of momentum factor is only significantly positive in only 9 months after portfolio formation. Hence, trading strategies in this chapter have the pre-formation of six months and post-formation periods of nine months.

To construct the winner and loser portfolios, we apply the method of Jegadeesh and Titman (1993, 2001). At the start of every month in the sample period, all stocks are ranked on the past six-month returns (from month t-1 to month t-6). Then, they are divided into five quintiles. The value-weighted returns on each quintile are computed for the following nine months. The top quintile portfolio with the highest past returns is called the winner quintile and the bottom quintile with the lowest past returns is called the loser quintile.

The trading strategies include portfolios with overlapping holding periods to enhance the tests' power (Jegadeesh and Titman, 1993, 2001; Byun et al., 2016). According to Jegadeesh and Titman (1993), this technique helps avoid the autocorrelation of the hedge portfolio returns. The return on a momentum portfolio in any month consists of returns on that quintile created in the current month as well as in the last eight months. For example, a September loser return is an equally weighted average of the first-month return on the loser built in the beginning of September, the second-month return on the loser formed in August, etc., the ninth-month return on the loser built in January. Similarly, an October loser return is an equally weighted average of the first-month return on the loser created in October, the second-month return on the loser built in September, etc., the ninth-month return on the loser formed in February. In other words, in any given month t, the strategy holds a series of portfolios that are selected in the start of this month and previous eight months. In addition, the strategy closes out the position initiated in month t-9. Hence, under this trading strategy, we revise the weights on 1/9 of the securities in the entire portfolio in any given month and carry over the rest from the previous month. In other words, rolling forward to the next month, we drop the oldest portfolio and add the newest portfolio.

All shares are also divided into five portfolios based on the estimated OR. The construction of these portfolios are similar to momentum portfolios. The only difference is that shares are sorted on the measure of overreaction instead of the past returns. We focus on the highest (lowest) OR quintile, which indicates the strongest overreaction on the positive (negative) side. Returns of portfolios ranked on the past returns and OR are displayed in the next section.

5.4. Results and Discussions

5.4.1. The momentum effect in Vietnam

The annual average returns of five momentum portfolios during 2009-2019 are presented in Figure 18. It is evident that momentum exists in Vietnam during 2009-2019. The annual returns fall monotonically from the winner to the loser. The winner portfolio delivers a highly positive return, at more than 16% per annum; while the annual average return of the loser is substantially lower, at only around 5%. We also focus on the return of a trading strategy that buys the winner portfolio and sells the loser portfolio. The WML (Winner minus Loser) strategy provides a positive return of roughly 11% yearly, which is significant at 10%. This result is in line with the result of Vo and Truong (2018). They report that a momentum strategy in which investors select a portfolio based on previous 6 months and hold for 9 months generates significant profit during 2007-2015.

Winners seem to be large and growth stocks, with an average capitalization of $191.24 million and an average market-to-book of about 2. It is the reason why momentum could explain the growth effect in Vietnam as documented in chapter 4.

By contrast, losers tend to have smaller capitalization, with an average of more than $100 million. Since the average value of M/B for losers is very close to 1, their book value of equity are likely to equivalent to their market values.

	Winner	2	3	4	Loser	WML
Annual average return (%)	16.052**	13.580*	8.995	5.920	4.805	11.247*
t-statistic	3.098	2.061	1.527	1.106	0.956	1.733
Capitalization ($ million)	191.24	169.78	132.33	100.00	111.43	-
Market-to-book	2.057	1.557	1.480	1.223	1.191	-

Note: We divide all stocks into five portfolio based on the past six-month returns. The annual average returns, the average values of market capitalization, market-to-book ratio are reported. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 18 - Analysis on portfolios ranked by the past returns

5.4.2. Overreaction and stock returns

Portfolios ranked on OR	1	2	3	4	5	1-5
Annual average return (%)	16.903***	11.482	9.617*	6.797	6.693	10.209*
t-statistic	3.378	1.650	2.071	1.494	1.187	1.749
OR	10.302	4.617	1.341	-2.006	-7.739	-
Capitalization ($ million)	148.363	139.91	131.22	119.88	119.71	-
Market-to-book	1.743	1.595	1.496	1.359	1.376	-

Note: We divide all stocks into five portfolio based on the estimated OR. The annual average returns, the average values of market capitalization, market-to-book ratio are reported. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 19 - Analysis on portfolios ranked by the estimated OR

Figure 19 displays the annual average returns of five portfolios sorted on the estimated OR from 2009 to 2019. Each portfolio is built by ranking all samples stocks based on the overreaction measure computed over the past six months. Portfolio 1 (upward overreaction) includes stocks with the highest values of OR, at an average of about 10.3. Meanwhile, stocks with the lowest values of OR are grouped to portfolio 5 (downward overreaction). The average OR for portfolio 5 is significantly negative, at close to -8, which implies that they have experienced strong downward overreaction.

There is minor difference in capitalization among OR-ranked portfolios. The largest average capitalization belongs to portfolio 1, at around $148 million; while the smallest average capitalization belongs to portfolio 5, at approximately $120 million. Similarly, the average market-to-book ratios for all OR-ranked portfolios are nearly the same, at about 1.5. Therefore, the return differential among five overreaction portfolios seems to be irrelevant to the size and value factors.

As shown in Figure 19, a monotonic relationship between the OR ranks and portfolio returns could be clearly observed. Stocks that are faced with strong upward overreaction provide the highest average return, at close to 17% annually. It is statistically significant at the level of 1%. In contrast, stocks that are faced with strong downward overreaction earn the lowest average return, at only about 6.7%. The last column reports the return on a zero-investment portfolio, that is long the upward-overreaction portfolio (portfolio 1) and short the downward-overreaction portfolio (portfolio 5). At the level of 10%, this zero-investment portfolio yields a significantly positive return of around 10.2% per year. These results imply that profitable long–short trading strategies could be implemented using our measure of overreaction, with an annualized return of 10.2%. Thus, the estimated measure of overreaction is likely to predict future stock returns. The higher the OR, the higher the average return.

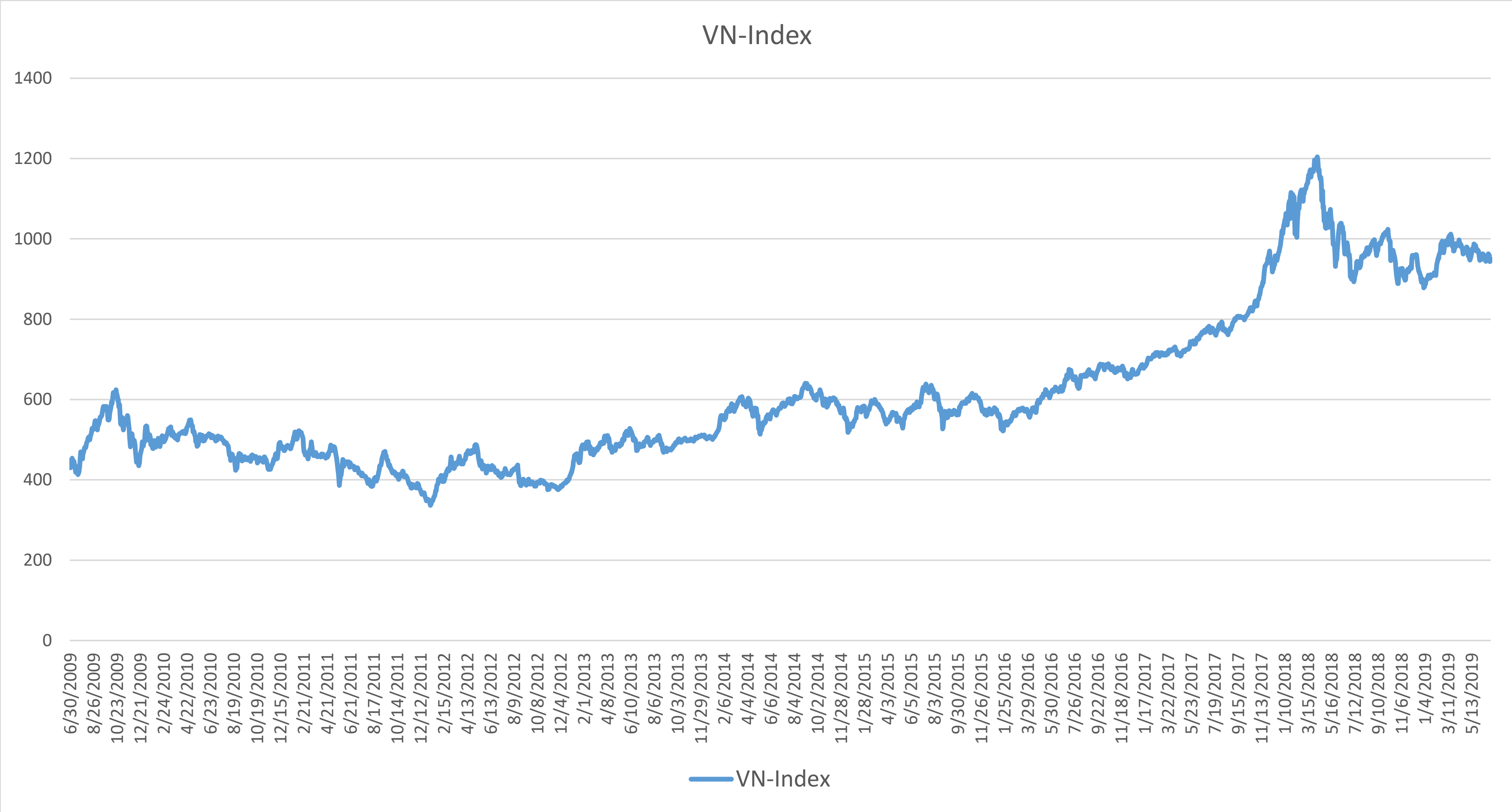

Figure 20 - The VN-Index from June 2009 to June 2019

We also estimate returns of trading strategies based on momentum and overreaction after excluding the bubble period. There is a bubble in the Vietnamese stock market between July 2017 and June 2018. The market index, VN-Index, rose dramatically by about 40% in only six months, from about 776 at the end of June 2017 to roughly 1100 at January 2018 (see Figure 20). Consequently, the VN-Index dropped rapidly to approximately 900 at June 2018. From July 2018 to June 2019, since the VN-Index fluctuated around 950, the Vietnamese stock market seems to be more stable.

Panel A. Returns of momentum portfolios for the entire period and after excluding bubble period						
	Winner	2	3	4	Loser	WML
Annual average return (%) (the entire period)	16.052**	13.580*	8.995	5.920	4.805	11.247*
t-statistic	3.098	2.061	1.527	1.106	0.956	1.733
Annual average return (%) (excluding bubble period)	15.782**	12.634*	8.037	3.852	3.531	12.251
t-statistic	2.744	1.743	1.24	0.696	0.633	1.704
Panel B. Returns of overreaction portfolios for the entire period and after excluding bubble period						
Portfolios ranked on OR	1	2	3	4	5	1-5
Annual average return (%) (the entire period)	16.903***	11.482	9.617*	6.797	6.693	10.209*
t-statistic	3.378	1.650	2.071	1.494	1.187	1.749
Annual average return (%) (excluding bubble period)	15.812**	10.296	7.983	6.276	4.767	11.045*
t-statistic	2.844	1.348	1.641	1.248	0.804	1.804

Note: This table reports the annual average returns of portfolios based on momentum and overreaction. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 21- Returns of momentum and overreaction portfolios for the entire period and after excluding bubble period

Since a bubble in Vietnam exists between July 2017 and June 2018, we calculate returns of five momentum portfolios and five OR-ranked portfolios after removing this period. The results are outlined in Figure 21. When the bubble period is removed, returns of all portfolios fall slightly. However, the momentum effect still exists. The annual returns decrease monotonically from the winner to the loser. The winner portfolio delivers a significantly high yearly return, at 15.782%; while the annualized average return of the loser is lowest, at only 3.531%. After removing the bubble, the return of a trading strategy that buys the winner portfolio and sells the loser portfolio rises by nearly 1% per annum, however its t-statistic drops marginally by 0.03.

Similarly, a monotonic relationship between the estimated OR and portfolio returns remains unchanged after we exclude the bubble period. As shown in Panel B of Figure 21, stocks that have experienced a stronger upward overreaction generate the higher average return. A long–short trading strategy using our estimated OR (portfolio 1-5) is profitable, at around 11.045% per year, which is slightly higher than the return for the whole period.

To sum up, it could be concluded that there is virtually no difference in the results after removing the bubble period during 2017-2018.

5.4.3. Overreaction and momentum

According to Daniel et al. (1998), if the level of overreaction remains unchanged, momentum does not exit. The key reason of momentum return is that investors become increasingly more confident about their private information as a result of biased self-attribution. Hence in this section, to investigate whether momentum exits after controlling for overreaction, we carefully compare trading strategies based on overreaction with price momentum strategies using adjusted returns and double sorts on past returns and estimated OR.

5.4.3.1. Benchmark-adjusted returns

If the underlying mechanism of return predictability based on past returns is overreaction as suggested by Daniel et al. (1998), our direct measure of overreaction should be a better predictor of future returns than past returns. Hence, we make a comparison between trading strategies based on past returns and OR. The benchmark-adjusted returns on one strategy are computed using returns on portfolios built by the remaining strategy. In other words, the portfolios' return created by one strategy is considered as a benchmark to estimate the benchmark-adjusted return of the other. For instance, to calculate the momentum-adjusted returns of OR quintiles, the return of each share is adjusted by subtracting the return of the momentum quintile where the share belongs. An example of calculation is given in Appendix A3. The raw returns and benchmark-returns of trading strategies based on momentum and overreaction are reported in Figure 22.

The raw returns of momentum and OR portfolios are nearly the same. The return of a trading strategy that is long winner stocks and short loser stocks (WML - Winner Minus Loser) is around 11.25%, with a t-statistic of 1.73. The return differential between the highest and lowest OR portfolios (portfolio 1-5) is about 10.21%, with a t-statistic of 1.75. Both strategies show the same raw return patterns. However, the benchmark-adjusted returns of two strategies are much different. As shown in Panel B of Figure 22, the benchmark-adjusted returns of overreaction portfolios still exhibit a monotonic decrease across the OR quintiles. The highest benchmark-adjusted return belongs to portfolio 1 with the highest values of OR. The benchmark-adjusted return on a zero-investment portfolio, that purchases the upward-overreaction portfolio (portfolio 1) and sells the downward-overreaction portfolio (portfolio 5), is significant at the level of 5%, at around 5.9%. By contrast, the benchmark-adjusted returns of momentum portfolios do not show a clear decrease from the winner to the loser. The WML adjusted return is only around 1.7% and it is statistically insignificant. Except for portfolio 4, the t-statistics of adjusted returns on momentum portfolios are very close to zero. It is evident that the profits of overreaction strategies subsume those of momentum strategies.

Panel A. Benchmark-adjusted returns of momentum portfolios						
	Winner	2	3	4	Loser	WML
Raw return (%)	16.052***	13.580**	8.995	5.920	4.805	11.247*
t-statistic	3.098	2.061	1.527	1.106	0.956	1.733
Benchmark-adjusted return (%)	1.692	0.419	-0.130	-3.124**	0.028	1.664
t-statistic	0.879	0.238	-0.064	-2.156	0.019	0.541
Panel B. Benchmark-adjusted returns of overreaction portfolios						
Portfolios ranked on OR	1	2	3	4	5	1-5
Raw return (%)	16.903***	11.482	9.617**	6.797	6.693	10.209*
t-statistic	3.378	1.650	2.071	1.494	1.187	1.749
Benchmark-adjusted return (%)	2.753	-0.694	-1.168	-1.973	-3.108	5.861**
t-statistic	1.546	-0.343	-0.833	-1.494	-1.680	2.178

Note: This figure displays the raw returns and benchmark-adjusted returns of portfolios ranked by the past returns and estimated OR. The benchmark-adjusted returns on one strategy are computed using returns on portfolios built by the remaining strategy (see Appendix A3). *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 22 - Benchmark-adjusted returns of momentum and overreaction portfolios

5.4.3.2. The CAPM- and Fama-French- adjusted returns

Panel A. The CAPM- and FF-adjusted returns of momentum portfolios						
	Winner	2	3	4	Loser	WML
The CAPM-adjusted returns (%)	10.477***	8.14***	3.905	2.266	2.11	8.087**
t-statistic	3.168	2.967	1.357	0.81	0.741	1.993
The FF-adjusted returns (%)	10.22***	7.993***	3.7	0.825	1.85	7.918**
t-statistic	3.098	2.89	1.24	0.259	0.233	1.976
Panel B. The CAPM- and FF-adjusted returns of OR portfolios						
Portfolios ranked on OR	1	2	3	4	5	1-5
The CAPM-adjusted returns (%)	12.106***	6.192**	5.53**	2.79	2.58	10.454**
t-statistic	3.977	2.252	2.16	0.993	0.781	2.162
The FF-adjusted returns (%)	11.926***	5.46**	4.821*	2.043	1.334	9.291**
t-statistic	3.929	1.973	1.784	0.686	0.389	2.000

Note: This figure presents the CAPM- and FF- adjusted returns, which are calculated based on the estimated regression intercepts or alphas. The White robust standard errors are estimated to deal with heteroscedasticity. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 23 - The CAPM- and FF- adjusted returns of momentum and OR portfolios

In this section, we estimate the CAPM- and Fama-French- adjusted returns of momentum and overreaction portfolios. To estimate the CAPM-adjusted returns, we run the following regression to estimate the beta:

$$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + \varepsilon_{it}$$

R_{it} is the return of the portfolio i for period t. R_{mt} is the market return, which is the return of VN-Index. R_{ft} is the yield on the one-year Vietnamese government bond. ε_{it} is the residual for period t. The CAPM risk-adjusted return is measured as $R_{it} - R_{ft} - \widehat{b_i} * [R_{mt} - R_{ft}]$

Likewise, the Fama-French-adjusted returns (FF-adjusted) are calculated by running the Fama-French three-factor regression:

$$R_{it} - R_{ft} = a_i + b_i * [\, R_{mt} - R_{ft} \,] + s_i * SMB_t + h_i * HML_t + \varepsilon_{it}$$

The formation of SMB and HML factor is identical to section 4.4.2. Descriptions of returns on explanatory factors are outlined in Figure 8. Based on the estimated beta and factor loadings, the FF-adjusted return is $R_{it} - R_{ft} - \hat{b}_i * [\, R_{mt} - R_{ft} \,] - \hat{s}_i * SMB_t - \hat{h}_i * HML_t$. The CAPM- and FF-adjusted returns of momentum and overreaction portfolios are reported in Figure 23.

Overall, there is a substantially decrease in returns of both trading strategies when controlling for asset pricing models. Since the FF three-factor model is better than the CAPM in term of explaining stock returns (as documented in section 4.5.2), the CAPM-adjusted returns are higher than the FF-adjusted returns for all portfolios. The pattern of risk-adjusted returns of both trading strategies is nearly the same as the pattern of raw returns. The adjusted-return drops monotonically from the winner to the loser (Panel A). Identically, Panel B also shows a monotonic decrease in adjusted-returns from portfolio 1 (upward overreaction) to portfolio 5 (downward overreaction).

The last column of Figure 23 shows that returns of both trading strategies are significant after adjusting to asset pricing models. The CAPM-adjusted return of a portfolio, which is long shares with upward overreaction and short shares with downward overreaction, is statistically significant, at nearly 10.5% per year. Its FF-adjusted return is around 9.3% annually, which is significant at the level of 5% with a t-statistic of 2. Similarly, both the CAPM- and FF-corrected returns for the WML

(Winner Minus Loser) are still significant at 5%. It is in line with Fama and French (1996); Grundy and Martin (2001); Wang and Wu (2011) and consistent with results of section 4.5.3.1. The asset pricing models are unlikely to capture the momentum profits. Notably, although the momentum strategy generates a higher raw return than the overreaction strategy (see Figure 21), the overreaction trading strategy beats the momentum in terms of risk-adjusted returns. In the CAPM, the adjusted returns for trading strategies based on overreaction and momentum are 10.454 and 8.087, respectively. Within the framework of the Fama-French three-factor model, the corrected return of the WML is close to 8%, which is lower than the adjusted return of overreaction strategy (9.291%).

5.4.3.3. Double-sorted portfolios

We also rank stocks by their past returns and estimated OR to investigate whether abnormal positive returns on the winner portfolio are actually concentrated in stocks with high OR. If the momentum effect arises from investors' overreaction, the stronger the upward overreaction, the higher the average return for stocks. Double-sorted portfolios are constructed as follows. Firstly, all stocks are divided into five groups based on past returns (or the estimated OR). Consequently, in each group, stocks are ranked into three sub-portfolios according to the estimated OR (or the past returns), which leads to a total of 15 sub-portfolios. In panel A of Figure 24, stocks are initially ranked on their past returns, then they are sorted on their estimated OR. In panel B, stocks are initially ranked on their OR, then they are sorted on their past returns.

As outlined in Panel A of Figure 24, when stocks are ranked on past returns and OR, an obvious positive relationship between the estimated OR and average returns is observed. From the winner to the loser, high-OR sub-portfolios provide significantly higher average returns than low-OR portfolios. For example, the average return on high-OR-winner portfolio is more than 27% per year, while the average return on low-OR-winner portfolio is substantially lower, at only approximately 9%. Hence, the superior returns on winner portfolio are concentrated in stocks that have experienced a strong upward overreaction. In all quintiles sorted by past returns, stocks that are faced with a stronger upward overreaction earn a higher average return than their counterparts. Therefore, the trading strategy based on overreaction provides significant profit even if experimental control is exercised over differences in past returns. It is consistent with the result of two previous sections.

Panel A. Average returns of portfolios ranked on past returns and OR					
	Winner	2	3	4	Loser
High OR	27.1%**	16.73%**	13.18%	8.22%*	5.92%
Neutral	16.89%	12.72%	8.67%	5.2%	4.6%
Low OR	8.95%	9.24%*	6.05%	0.85%	1.42%
High-Low	18.15%*	7.49%*	7.13%	7.37%*	4.5%
Panel B. Average returns of portfolios ranked on OR and past returns					
	1	2	3	4	5
High past returns	20.12%**	17.18%*	9.17%	7.65%*	7.55%
Neutral	12.58%	13.53%	12.52%*	6.18%	4.21%
Low past returns	23.62%**	10.11%	11.28%	3.43%	5.56%
High-Low	-3.5%	7.07%	-2.11%	4.22%*	1.99%

Note: All stocks are divided into 15 different sub-portfolios. First, they are initially sorted on their past returns, then in every momentum portfolio, stocks are ranked on their estimated OR. The returns of 15 sub-portfolios are reported in Panel A. Similarly, stocks are put into five OR-ranked portfolios, then each portfolio are divided into three sub-portfolios based on their past returns. The annual average returns of 15 sub-portfolios are displayed in Panel B. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively.

Figure 24 - Average returns of double-sorted portfolios

However, as shown in Panel B of Figure 24, when stocks are ranked on their OR and past returns, no linear relationship between past returns and average returns is apparent. For example, in the first portfolio, stocks with low past returns earn the highest average return, at about 23.62%, whereas the annual average return of sub-portfolio with high past returns is lower, at around 20%. Meanwhile, in the second, fourth, and fifth portfolios, sub-portfolios with high past returns provides the highest average returns. There is no pattern in the average returns of portfolios sorted on past returns within each overreaction quintile. Momentum virtually disappears when returns are controlled for differences in estimated OR.

To sum up, it could be concluded that most of the momentum profitability is driven by the overreaction of investors.

5.5. Conclusion

Although the solid empirical proof of momentum is documented in various stock markets, there are a great number of debates among academics with respect to the source of momentum profit. The momentum profitability cannot be explained by the risk-based point of view (Fama and French, 1996; Grundy and Martin, 2001; Cooper et al., 2004). From the behavioural perspective, the delayed overreaction of Daniel et al. (1998) is viewed as one of the leading explanations of momentum (Jegadeesh and Titman, 2001). Motivated by models of Daniel et al. (1998) and Byun et al. (2016), we propose a measure of overreaction in Vietnam based on trading volume and the sign of stock returns. A combination of high trading volume and positive returns indicates the overreaction to positive private information, then stock prices are pushed above their intrinsic values. Conversely, a high trading volume combined with negative returns implies the overreaction to negative private information, which forecasts a decrease in share prices.

The results of this chapter provide three main insights. Firstly, the momentum effect is documented in Vietnam during 2009-2019. The winner portfolio delivers a highly positive return, at more than 16% per annum; while the annual average return of the loser is substantially lower, at only around 5%. It is consistent with the result of Vo and Truong (2018). Secondly, the estimated measure of overreaction seems to predict future stock returns. Stocks that have been faced with a stronger upward overreaction earn the higher average returns. A trading strategy that buys the upward-overreaction portfolio and sells the downward-overreaction portfolio deliver a significantly positive return of approximately 10.21% per year. Finally, while the momentum profit disappears after controlling for the effect of overreaction, the trading strategy based on overreaction provides significant returns even after we adjust for the momentum effect. The overreaction trading strategy also generates higher risk-adjusted returns within the framework of the CAPM and Fama-French three-factor model. Furthermore, using double sorts, we find that holding past returns constant, the average returns of portfolios increase monotonically with their measure of overreaction. On the other hand, there is generally no significant difference between the average returns of portfolios sorted on past returns within each overreaction quintile. The evidence we uncover sheds light on explanations of momentum in Vietnam, which is consistent with the overreaction story based on overconfidence of Daniel et al. (1998).

6. The size effect and default risk in the Vietnamese stock market

The literature is inconclusive on the source of the size effect. This chapter contributes to extant studies by investigating the relationship between the size premium and default risk in Vietnam, an important frontier emerging market. The debt-to-equity ratio and distance-to-default of Merton (1974) are used as distress-risk proxies. We discover that the small portfolio delivers the highest average return based on more than 300 listed stocks over 2009-2019. The excess return on the small portfolio is concentrated in firms with high distress risk. Furthermore, neutral size factors are built to dissect returns on the Fama-French size factor from the default risk premium. Empirical results prove that the explanatory power of the size factor is negatively affected when the default-risk neutrality is applied. Given this backdrop, the size premium in Vietnam is likely to be compensation for distress risk, consistent with a risk-based point of view

6.1. Introduction

Since Banz (1981) discovered, the size effect, the tendency of small stocks to outperform big stocks, has become a famous anomaly in the stream of literature on market finance. Subsequently, the size effect is documented in numerous developed and emerging markets such as the US, the UK, France, Japan, China, Korea. Despite empirical proof of the size effect, the reason behind the excess return of small stocks is controversial. Various academics and professionals suggest that small companies are faced with higher default risk than big companies (Chan and Chen, 1991; Fama and French, 1996). Small firms' stocks tend to move together, and then they cannot diversify their risk (Campbell et al., 2008). As a result, investors should be compensated for a risk premium for holding small stocks. Nevertheless, Campbell et al. (2008) and Groot and Huij (2018) reveal that the bankruptcy risk is unlikely to drive the size premium in the US. When the link between the size effect and default risk is comprehensively investigated in developed markets, particularly the US, it has not been evaluated yet in Vietnam, an important frontier emerging market. It is necessary to examine whether the size is a proxy for the distress-risk factor in Vietnamese stock returns. Thus, this chapter investigates the relationship between the size premium and default risk in this market.

The equity market of Vietnam was officially established on 28th July 2000 with the birth of the Ho Chi Minh stock exchange. The recent decade has observed a substantial growth of this stock market. From a limited market capitalization of about $33 billion in 2009, the total market capitalization reached roughly $180 billion at the end of 2020, accounting for more than 68% of the national GDP. With modern trading systems and applications, the liquidity of the Vietnamese market is also enhanced significantly. Automatically electronic platforms conduct about 90% of transactions. The total value of traded stocks rose rapidly, from nearly $8 billion in 2009 to about $57 billion in 2020. According to Morgan Stanley Capital International, Vietnam is categorized as one of 28 frontier emerging markets. It is also grouped with the CIVETS[4] countries, considered favored emerging markets thanks to dynamic economies, young populations, and political stability (Korkmaz et al., 2012). Although the Vietnamese stock market has gradually achieved the development level of other advanced markets worldwide, there is still a long pace for Vietnam to achieve the global financial standard. A large number of Vietnamese investors tend to follow herd behavior instead of rational behavior (Vo and Phan, 2017). Despite the domination of the biggest firms in terms of trading volume and market capitalization (Quach et al., 2019), investing in the low-cap stocks generates a significantly higher return (Nguyen et al., 2015; Nguyen and Nguyen, 2016). Therefore, the question is whether Vietnamese investors rationally evaluate stocks with low capitalization. In other words, this research examines whether investors charge a premium for holding small shares with higher distress risk, shedding further light on how Vietnamese investors price stocks.

[4] CIVETS countries are: Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa.

There are two main motivations for this research. Firstly, even though several studies investigating the size effect are carried out in the Vietnamese market, their sample composition is disadvantageous to some extent. Only the biggest firms (Quach et al., 2019) or the service sector firms (Nguyen and Nguyen, 2016) are taken into consideration. Furthermore, the sample period before 2009 may lead to inaccurate findings due to a small number of Vietnamese listed companies and the financial crisis in 2008. Hence, the chapter fills this gap by intensively re-examining the size effect among all Vietnamese non-financial stocks between 2009 and 2019. During this period, the stock market represented the Vietnamese economy and stabilized thanks to the economic recovery. Secondly, as reported in chapter 4, only the size (SMB) factor includes incremental information on Vietnamese stock returns among four Fama-French mimic factors. Therefore, it is necessary to investigate the link between the size premium and bankruptcy risk in this market, which has not been analyzed yet in any published paper.

Some interesting findings are reported in this chapter. During the sample period, investing in small stocks provides the highest average return, at about 19.3% per year. The size premium in Vietnam seems to follow the same trends documented in other stock markets. To assign stocks into different risk-level portfolios, the debt-to-equity (D/E) ratio and distance-to-default (DD) of Merton (1974) are used. The second finding is that the superior return on the small portfolio is concentrated in high-risk stocks. When the risk proxy is the DD, the average return on small high-risk shares is more than 35% per annum, close to four times the average return on small low-risk shares. Finally, adopting the technique suggested by Groot and Huij (2018), stocks are initially ranked on their risk proxies before being divided into small and big portfolios to construct neutral size factors. As a result, these small and big portfolios have virtually equal distress-risk proxies. Neutral SMB factors are less exposed to bankruptcy risk than the ordinary SMB of Fama and French (2016). The explanatory power of the SMB factor decreases when the default-risk neutrality is imposed. Especially, the DD-neutral SMB is likely to be an insignificant factor. To sum up, the size premium in Vietnam seems to arise from distress risk, which corroborates the risk-based explanation.

The chapter consists of six sections. The literature overview is introduced in the second. The third section summarises data selection and estimation of distress-risk proxies. The size effect and its relationship with default risk are analyzed in the next two sections. The final gives concluding remarks.

6.2. Literature review

A variety of papers report that stocks with low market capitalization generate abnormal positive returns. This phenomenon is known as the size effect documented initially by Banz (1981). Analyzing firms listed in the New York stock exchange, he states that investing in stocks with the lowest capitalization may lead to an excess return of 0.4% per month, which is higher than other stocks. Later on, the superior returns of small shares in the US are discovered in a large volume of research: Reinganum (1981), Keim (1983), Lamoureux and Sanger (1989), Fama and French (2016). The size effect is also confirmed in other developed markets, namely the United Kingdom, France, Germany, Japan, and emerging markets, namely Singapore, Korea, Taiwan, China. (Van Dijk, 2011; Leite et al., 2018). Evidence of the size premium in numerous markets over various periods raises no concern about data mining.

Despite solid proof of the size effect in many equity markets, academics and practitioners remain inconclusive as to whether the superior returns on small stocks are compensation for financial distress risk. By examining the structural characteristics, Chan and Chen (1991) declare that low-cap companies often have inferior production efficiency and high leverage, which implies a higher default risk. Since a three-factor model with the market, size, and value factors captures a vast majority of variability in the US stock returns over 1963-1991, the size might be a proxy for distress risk (Fama and French, 1996). The effect of bankruptcy risk on stock returns is evaluated by Vassalou and Xing (2004). As the size premium is only documented in the highest risk quintile and smaller companies have considerably higher distress risk, they conclude that default risk accounts for the size effect. Gharghori et al. (2009) state that the size effect in the Australian stock market only exists in firms with high default risk, then the size premium is a default premium.

According to Hwang et al. (2010), the CAPM augmented with a credit spread factor representing distress risk could explain the size effect in the US from 1934 to 2006. By double-sorting Brazilian stocks by size and default risk levels over the period between November 1992 and December 2007, Abinzano et al. (2014) find that in the small size group, the average return differential between high and low default probability portfolios is statistically significant, at 1.16% per month. Consequently, the size effect arises from bankruptcy risk. According to Elgammal et al. (2016), the default premium has explanatory power for the size premium in the US stock returns from 1982 to 2011.

On the other hand, many papers question the relation between the size premium and bankruptcy risk. Using accounting models to measure default risk, Dichev (1998) reports that low-risk stocks deliver higher average returns from 1981 to 1995 in the US. In other words, the default factor is improbable to be the source of size premium, which is similar to the conclusion of Campbell et al. (2008). Although financially failure stocks have higher size factors than those with lower distress risk, they do not provide higher returns. Hur et al. (2014) declare that payment to size does not represent payment to distress risk since the relationship between size and returns is significant only in the down market. Recently, Groot and Huij (2018) show that the US's size premium cannot be explained by bankruptcy risk irrespective of estimating the default probability by accounting and structural models, credit ratings, or credit spread. Furthermore, the explanatory power of size factor to stock returns is not attributed to distress risk.

Although the size effect in Vietnam is examined in several papers, their findings are inconsistent. Ranking stocks on market capitalization, Chin and Nguyen (2015) declare that the return differential between big and small firms is insignificant from 2006 to 2014. By contrast, a monthly size premium of about 0.38% between 2007 and 2015 is reported by Nguyen et al. (2015). A possible reason behind these contradictory results is that the data sample of Nguyen et al. (2015) includes all stocks traded on Ho Chi Minh and Hanoi stock exchanges, whereas Chin and Nguyen (2015) focus on firms listed on the Ho Chi Minh stock exchange. Analyzing data of 33 listed firms in the service sector, Nguyen and Nguyen (2016) point out a size effect between 2009 and 2014. Meanwhile, Quach et al. (2019) cannot find reliable evidence of a size premium after examining 60 biggest Vietnamese stocks from 2010-2014. There are several important caveats to these papers. The first is the sample selection. Because of a crisis during 2007-2008 and a bubble during 2005-2007, Vietnamese stock price data before 2009 may include a great deal of noisy information. Therefore, the findings of Chin and Nguyen (2015) and Nguyen et al. (2015) could be incorrect. Meanwhile, Nguyen and Nguyen (2016) and Quach et al. (2019) only investigate the service sector and 60 largest firms. As a result, more studies should be carried out to give a more intensive picture of the Vietnamese stock market. Secondly, none of these papers explains the size effect. Furthermore, as documented in section 4.5.2, SMB is the only significant explanatory factor among four Fama-French mimic factors. Given this backdrop, our research's key aim is to investigate the size effect and its link with distress risk in Vietnam.

6.3. Data sample and default risk proxies

6.3.1. Data sample

Year	Number of stocks	Year	Number of stocks
2009	124	2015	265
2010	187	2016	279
2011	216	2017	304
2012	238	2018	319
2013	248	2019	340
2014	250		

Figure 25 - The number of sample stocks

The data sample is the same as chapter 4 and chapter 5. We focus on the Ho Chi Minh stock exchange, accounting for more than 90% of the Vietnamese market capitalization. Most stocks listed in the Hanoi stock exchange belong to medium and small-sized firms, then their stock prices are very likely to be manipulated. The data sample includes more than 300 non-financial shares in the Ho Chi Minh stock exchange. According to Fama and French (1992), the high leverage of financial firms does not have the same meaning as non-financial firms. For non-financial firms, high leverage more likely implies a higher default risk. Hence, if the sample includes financial firms, they would be classified as firms with high distress risk, although their actual default risk might not be high. The 2009-2019 period is selected because many large companies representing the Vietnamese economy are only listed from 2009. Furthermore, due to the market bubble over 2005-2007 and the financial crisis in 2008, stock prices before 2009 may contain a great amount of noise, which leads to possible inaccuracies. Adjusted stock prices are collected from DataStream, while accounting figures are obtained from the DataStream and Fiingroup, a local data provider. Sample stocks must meet the following criteria. Firstly, their financial reports must be audited, and their accounting data from both data sources must be identical. Secondly, illiquid stocks with no transaction in ten consecutive trading days are excluded. Finally, if the absolute return of a share in a particular week is more than 35%, it is also removed from the sample.

6.3.2. Default risk proxies

Since the bond market is infant age, and there is no reliable credit rating system for listed firms in Vietnam, it is not easy to obtain credit ratings or spread credit. Hence, there are two default risk proxies in this research. The first is the debt-to-equity (D/E), which equals total liabilities divided by the book value of equity. According to Berk and DeMarzo (2013), the amount of bankruptcy risk depends on leverage, which is commonly measured by the firm's debt-to-equity ratio. To investigate the relationship between size premium and default risk, several papers use the D/E as a default risk proxy, such as Chan and Chen (1991), Groot and Huij (2018).

The second is the distance-to-default (DD) developed by Merton (1974). According to Jessen and Lando (2015), Afik et al. (2016), although often underestimating the default probability, the DD successfully classifies firms' distress risk, which is suitable for our purpose. We do not aim to calculate the default probability accurately, but only rank firms on the default risk to examine the link between the size premium and default risk. In Vietnam, Vuong (2019) documents that the Merton model is qualified for bankruptcy risk ranking with roughly 45% accuracy. Vo et al. (2019) also declare that both accounting risk proxies (ex: debt-to-equity) and DD appropriately measure Vietnamese listed firms' financial distress during 2007-2017.

Merton (1974) states that if the market value of company assets (V_t) is lower than its debt due (D) at time T, it will go bankrupt. The assets value (V) is assumed to follow a geometric Brownian motion:

$$dV = \mu_V V dt + \sigma_V V dz$$

Where μ_V and σ_V are the expected return and volatility of V, which are assumed to be constants. z follows a Wiener process.

Thanks to the Itô's lemma, a function G = lnV follows a generalized Wiener process with a constant drift rate of $\left(\mu_V - \frac{\sigma_V{}^2}{2}\right)$ and a constant variance of $\sigma_V{}^2$ (Hull, 2015). Hence:

$$\ln V_t \sim N\left(\ln V_0 + \left(\mu_V - \frac{\sigma_V{}^2}{2}\right) * T, \sigma_V{}^2 * T\right)$$

At time T, the chance that V_t is less than D would be:

$$P(V_t < D) = P\left(\ln\left(\frac{V_t}{D}\right) < 0\right) = N\left(\frac{\ln\left(\frac{V_0}{D}\right) + \left(\mu_V - \frac{\sigma_V{}^2}{2}\right) * T}{\sigma_V * \sqrt{T}}\right)$$

N is the cumulative standard normal distribution function. σ_V and μ_V are the volatility and expected return of V. The expected return is assumed to equal the riskless rate r. The DD is usually estimated in one year, then T equals one. Therefore, DD is defined as:

$$\frac{\ln\left(\frac{V_0}{D}\right) + \left(r - \frac{\sigma_V{}^2}{2}\right)}{\sigma_V} \quad \textbf{(1)}$$

The DD gauges how many standard deviations a company is far away from bankruptcy. A lower DD indicates a higher default risk. Since the assets value and its variance cannot be directly observed, they are estimated by solving two non-linear equations. Following Merton (1974), the market value of a firm' equity (E_0) is regarded as a one-year European call option on the value of its assets. The strike price is the debt due after one year. Hence, the first equation of Black and Scholes (1973) is:

$$E_0 = V_0 . N(d_1) - e^{-r} . D . N(d_2) \quad \textbf{(2)}$$

$$d_1 = \frac{\ln\left(\frac{V_0}{D}\right) + \left(r + \frac{\sigma_V{}^2}{2}\right)}{\sigma_V}$$

$$d_2 = d_1 - \sigma_V$$

The second equation is the relation between the assets volatility (σ_V) and the equity volatility (σ_E) (Merton, 1974) (see Appendix A5):

$$V_0\ \sigma_V \frac{\partial E_0}{\partial V_0} = E_0 \sigma_E$$

Under the Black-Scholes formula, $\frac{\partial E_0}{\partial V_0} = N(d_1)$ (Campbell et al., 2008) (see Appendix A5), then:

$$V_0\ \sigma_V N(d_1) = E_0 \sigma_E \quad \textbf{(3)}$$

Two equations (2) and (3) are simultaneously solved with the following variables. E_0 is the market capitalization today, which is the number of outstanding shares multiplying its price. r is the yield on the Vietnamese one-year government bond. D is the due debt after one year, half of the long-run debt plus the current debt. It considers that a proportion of long-term debt may not mature after one year (Campbell et al., 2008). The volatility of equity is obtained from the daily variability of stock returns:

$$\sigma_E = \mathrm{std}\left[\frac{P_i - P_{i-1}}{P_{i-1}}\right]\sqrt{n}$$

P_i is the stock price at day i. n is the number of trading days during this year. Std[.] stands for standard deviation. This annualized method is commonly used in the estimation of distance-to-default (Jessen and Lando, 2015, Afik et al., 2016)

Based on the estimated value of assets (V_0) and its volatility (σ_V), the DD is computed for each stock using equation (1).

6.4. The size premium and default risk

6.4.1. The size effect in Vietnam

This section investigates returns on size-ranked portfolios in the Vietnamese stock market. From June 2009, shares are divided into five size-ranked quintiles based on their capitalization. Subsequently, the value-weighted returns on five quintiles are calculated for the subsequent six months[5]. Each quintile portfolio could be denoted as a trading strategy for buying stocks with a certain capitalization group in June (December) and holding them for the next six months. At the beginning of January (July), proceeds from disposition are put into a similar capitalization group. The average capitalization, D/E ratio, and DD are also computed for each portfolio. This process is repeated semi-annually from June 2009 to June 2019.

	1-Big	2	3	4	5-Small	All
Annual average return (%) (the entire period)	12.15	5.83	11.39	11.75	19.34	-
Annual average return (%) (excluding bubble period)	9.73	5.65	10.14	10.57	16.52	-
Average capitalization ($ million)	642.84	56.44	26.29	13.41	5.60	148.92
Debt-to-equity ratio	1.25	1.18	1.44	1.79	1.97	1.53
Distance-to-default	5.32	4.68	4.26	3.66	2.98	4.18

Note: All stocks are divided into 5 portfolios by their capitalization. The annual average return, the average values of market capitalization, debt-to-equity ratio, and distance-to-default for each portfolio are reported. As shown in section 5.4.2, since a bubble in Vietnam exists between July 2017 and June 2018, we calculate returns for the entire period and after removing the bubble period.

Figure 26 - Analysis of five size-ranked quintiles

[5] Vassalou and Xing (2004); Groot and Huij (2018) sort stocks monthly, which leads to high transaction costs. As mentioned in chapter 4, ranking stocks twice a year seems to be more reasonable in Vietnam.

Except for the big quintile[6], it is obvious that the annual average return increases monotonically from the second to the small quintile. From 2009 to 2019, the annual average return on the small portfolio is 19.34%, which is nearly doubled the average return of the fourth quintile. Since small-cap stocks generate the highest return than remaining stocks, the size effect is documented in Vietnam. After excluding the bubble period during 2017-2018, returns of all portfolios decline slightly, but the return pattern remains unchanged. The small portfolio still yields the highest return, at 16.52% per annum. Hence, evidence of the size premium is robust even after we adjust for the bubble period. Both distress risk proxies imply that holding small shares is riskier. On average, small firms' total liabilities are approximately two times their book equity, while the D/E ratio for the big and second quintiles is around one. Small companies are roughly 1.2 (=4.18 minus 2.98) standard deviations closer to their default points compared to the average stocks. It is consistent with Chan and Chen (1991) and Vassalou and Xing (2004), who document that low-cap firms have higher leverage and bankruptcy likelihood.

6.4.2. The size premium and default risk

Adopting Groot and Huij (2018) method, we sort stocks by their capitalization and risk proxies to examine whether abnormal positive returns on small portfolios are actually concentrated in high-risk stocks. Because low-risk firms are usually bigger than high-risk ones, a triple-sorted technique is used to ensure a slight difference in market capitalization between low- and high-risk portfolios. Firstly, stocks are divided into five size-ranked quintiles. Secondly, shares are ranked again into three small, mid, and big groups in each quintile based on their market caps. Consequently, stocks are ranked by their risk proxies in every group, which leads to three subgroups: low-, mid- and high-risk subgroups. Finally, small-cap low-risk, mid-cap low-risk, and big-cap low-risk subgroups are merged. An identical process is applied for mid- and high-risk categories (An illustration of triple-sorted method is given in Figure 32). Finally, there are three risk sub-portfolios in each quintile, leading to 15 size-risk sub-portfolios in total. Similarly, this procedure is repeated

[6] The big portfolio generates a high return because of the momentum effect (see Appendix A4).

every six months. The value-weighted annual average returns, mean capitalization and risk proxies are displayed in Figure 27 and Figure 28.

Panel A: Annual average return					
	1-Big	2	3	4	5-Small
High risk	11.8%	2.53%	17.63%	12.22%	24.12%
Mid	7.4%	8.54%	10.66%	12.76%	19.57%
Low risk	20.19%	6.95%	8.35%	11.54%	16.24%
High-Low	-8.39%	-4.41%	9.28%	0.68%	7.88%
Panel B: Average size ($ million)					
	1-Big	2	3	4	5-Small
High risk	672.11	55.88	26.39	13.47	5.56
Mid	573.37	56.35	26.20	13.52	5.70
Low risk	675.31	56.98	26.29	13.22	5.62
High-Low	-3.20	-1.10	0.11	0.25	-0.06
Panel C: Average debt-to-equity ratio					
	1-Big	2	3	4	5-Small
High risk	2.37	2.39	2.84	3.57	4.07
Mid	0.99	0.94	1.11	1.12	1.34
Low risk	0.36	0.34	0.37	0.34	0.41
High-Low	2.01	2.05	2.47	3.23	3.66

Note: We divide all stocks in to 15 sub-portfolios by their capitalization and debt-to-equity ratios. The annual average return, the average values of market capitalization, debt-to-equity ratio, and distance-to-default for 15 sub-portfolios are reported.

Figure 27 - Size effect controlled by the debt-to-equity ratio

Thanks to a triple-sorted technique, the average sizes of low- and high-risk portfolios are virtually equal. For example, in the small quintile, the average capitalization for all sub-portfolios are nearly the same, at around $5.6 million (Figure 27 and Figure 28). Hence, any return differences between sub-portfolios in the same size segment cannot be attributed to differences in market capitalization.

Panel A: Annual average return					
	1-Big	2	3	4	5-Small
High risk	17.97%	6.01%	19.25%	18.41%	35.82%
Mid	7.85%	3.49%	13.37%	14.42%	18.19%
Low risk	21.04%	7.94%	5.84%	4.41%	8.94%
High-Low	-3.07%	-1.93%	13.41%	14.00%	26.88%
Panel B: Average size ($ million)					
	1-Big	2	3	4	5-Small
High risk	591.81	55.95	26.33	13.29	5.51
Mid	619.94	56.82	26.26	13.35	5.64
Low risk	722.30	56.59	26.25	13.56	5.66
High-Low	-130.49	-0.64	0.08	-0.27	-0.16
Panel C: Average distance-to-default					
	1-Big	2	3	4	5-Small
High risk	3.12	2.60	2.37	2.13	2.05
Mid	4.71	3.95	3.50	3.17	2.67
Low risk	8.44	7.53	6.98	5.53	4.28
High-Low	-5.31	-4.93	-4.60	-3.40	-2.22

Note: We divide all stocks in to 15 sub-portfolios by their capitalization and distance-to-default. The average values of market capitalization, debt-to-equity ratio, and distance-to-default for 15 sub-portfolios are reported.

Figure 28 - Size effect controlled by distance-to-default

If distress risk is the key reason for size premium, the lower the risk, the lower the average return for small stocks. High-risk firms beat low-risk firms in three lowest-cap quintiles when the D/E ratio is viewed as the distress proxy. On average, small firms with high leverage generate 7.88% higher returns than those with lower leverage. Similarly, the return on a small sub-portfolio with low DD is substantially high, at about 36% per annum, which equals approximately four times the return of a sub-portfolio with high DD. We observe a positive relationship between default risk and stock returns from the third to small quintiles for both default risk proxies. Since bankruptcy risk is unlikely to drive returns on big shares, low-risk stocks provide higher returns for the big and second quintiles regardless of risk proxies. As a result, it could be concluded that default risk is the main source of the excess return on small stocks in Vietnam, which is similar to the Brazilian stock market (Abinzano et al., 2014). It is different from Groot and Huij (2018), who postulate that the size premium is not associated with the default risk in the US.

6.5. The size factor and default risk

According to the results of section 4.5.2, the size (SMB) factor is the only Fama-French mimic factor that contains additional information on expected returns. In this section, we examine whether the explanatory power of the SMB is adversely affected when the default-risk neutrality is applied in factor formation. Following Fama and French (2016), the SMB is:

$$\text{SMB} = 1/3 \; * \; (\text{SMB}_{\text{M/B}} + \text{SMB}_{\text{OP}} + \text{SMB}_{\text{Inv}})$$

The $\text{SMB}_{\text{M/B}}$ is calculated from six value-weighted portfolios ranked on capitalization and market-to-book (M/B). Stocks are assigned to big and small groups based on market cap. In the big group, 30% of stocks with the highest (lowest) M/B ratios are labelled as Big-Growth (Big-Value), while the remaining stocks are placed into the Big-Neutral. An identical process is applied for the small group. Portfolios are rebalanced semi-annually. Then:

$$\text{SMB}_{\text{M/B}} = 1/3 \; * \; (\text{Small-Growth} + \text{Small-Neutral} + \text{Small-Value} \\ - \text{Big-Growth} - \text{Big-Neutral} - \text{Big-Value})$$

Similarly, the SMB_{OP} (SMB_{Inv}) is estimated based on six portfolios ranked on capitalization and operating profitability (growth of total assets). Firms with the highest (lowest) operating profit margins are labelled as robust (weak) stocks, while stocks with the lowest (highest) growth rates of assets are placed into conservative (aggressive) portfolios. Then:

$$\text{SMB}_{\text{OP}} = 1/3 \; * \; (\text{Small-Robust} + \text{Small-Neutral} + \text{Small-Weak} \\ - \text{Big-Robust} - \text{Big-Neutral} - \text{Big-Weak})$$

$$\text{SMB}_{\text{Inv}} = 1/3 \; * \; (\text{Small-Conservative} + \text{Small-Neutral} + \text{Small-Aggressive} \\ - \text{Big-Conservative} - \text{Big-Neutral} - \text{Big-Aggressive})$$

The SMB factor with default-risk neutrality is built as suggested by Groot and Huji (2018). Firstly, stocks are ranked into three groups on their risk proxies: the high-, mid- and low-risk portfolios. Secondly, to estimate the neutral $SMB_{M/B}$, shares are divided into six sub-portfolios based on capitalisation and M/B ratio in each group. The size and M/B breakpoints are identical to the SMB formation discussed above. Finally, each Size-M/B portfolio's return is the average return of three sub-portfolios with different risk levels. For example, the return on the Big-Value:

Big-Value = 1/3 $*$ (High-Risk Big-Value + Mid-Risk Big-Value + Low-Risk Big-Value)

Then, the neutral $SMB_{M/B}$ is calculated using the formula of Fama and French (2016). The neutral SMB_{OP} and SMB_{Inv} are built similarly, and the neutral SMB is also the average return of $SMB_{M/B}$, SMB_{OP}, and SMB_{Inv} with distress-risk neutrality. Since stocks are firstly sorted on their risk proxies, distress-risk levels of big and small portfolios are nearly the same as shown in Figure 29.

The test assets are five size-ranked portfolios in section 6.4.1 and six portfolios ranked on capitalization and market-to-book (M/B). In chapter 4, we run Barillas and Shanken's (2017) redundancy test for the Vietnamese stock market. Since the regression intercepts of the market, size, and momentum factor are statistically significant, they are relevant explanatory factors to the Vietnamese stock returns. By contrast, the intercepts of value, profitability, and investment factors are indistinguishable from zero at 10% and 5% significance levels. Consequently, they add no incremental information and should not be included in the asset pricing model. As a result, the test model is a three-factor model:

$$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + s_i * SMB_t + w_i * WML_t + \varepsilon_{it} \quad \textbf{(4)}$$

R_{it} is the return of the portfolio i for period t. R_{mt} is the return on the VN-Index, which is viewed as the Vietnamese market portfolio. R_{ft} is the yield on the Vietnamese one-year government bond. WML is a momentum factor with the pre-formation and holding periods of six months[7]. There are 515 weekly observations between June 2009 and June 2019 for each time series. As argued in chapter 4, the weekly data interval is chosen because of several reasons. First, only stock prices at

[7] According to the results of section 4.4.3, in Vietnam, the momentum factor with a pre-formation period of six months generates a higher average return than a pre-formation period of eleven months.

the start and the end of every month are used to estimate monthly returns, while stock prices in a frontier market like Vietnam might fluctuate considerably in a month. Then the variability in stock prices would be thoroughly tracked with the weekly interval. Second, there are only more than 100 monthly observations. Finally, estimating multifactor models with monthly data might lead to inefficient coefficients due to a high autocorrelation in residuals. Descriptive statistics of explanatory factors are reported in Figure 29.

	R_m-R_f	SMB	SMB D/E neutral	SMB D/D neutral	WML
Mean (%)	0.075	0.085	0.05	0.006	0.129
Median (%)	0.25	0.05	0.03	-0.03	0.15
Maximum (%)	11.51	5.15	5.47	6.31	4.32
Minimum (%)	-11.88	-5.89	-6.04	-4.85	-5.49
STD (%)	2.82	1.53	1.56	1.54	1.46
Skewness	-0.38	-0.08	-0.01	0.11	-0.27
Kurtosis	4.92	3.46	3.47	3.67	4.42
Jarque-Bera	91.06	5.05	4.69	10.60	49.80
Probability	0.00	0.08	0.10	0.00	0.00
D/E	-	0.57	0.04	0.33	-
DD	-	-1.62	-1.29	-0.05	-
Observations	515	515	515	515	515

Note: The figure presents the descriptive statistics of time-serries returns on explanatory factors. The construction of the R_m - R_f, SMB, and WML factors are given in section 4.4.2 and section 4.4.3, while SMB D/E and D/D neutral factors are the neutral size factors. STD stands for the standard deviation of returns. Probability is the p-value of the Jarque-Bera test with the null hypothesis that returns are normally distributed. The D/E and DD are the average difference between big portfolios and small portfolios constructed for factor formation.

Figure 29 - Descriptive statistics of explanatory variables

Before neutralizing, the average D/E and DD differences between small and big portfolios are 0.57 and -1.62, respectively. It indicates that small stocks have higher distress risk, or the standard SMB is exposed to default risk, which is consistent with the result of section 6.4.1. By contrast, the distress-risk neutral factors are less exposed to default risk. Thanks to the risk-neutral technique, the difference of risk proxies between big and small portfolios constructing neutral factors is very close to zero.

After neutralizing, the SMB premium decreases substantially. The weekly mean return on standard SMB is 8.5 basis points, whereas the average returns on D/E and DD neutral factors are only 5 and 0.6 basis points, respectively. It implies that default risk might be the source of size premium. Since correlations among explanatory variables are always smaller than 0.7, multicollinearity is not presented (see Figure 30). Correlations between the standard and neutral SMB factors are 0.95 and 0.83, which are nearly the same as a result in the US market (Groot and Huij, 2018).

	R_m-R_f	SMB	SMB D/E neutral	SMB DD neutral	WML
R_m-R_f	1.00				
SMB	-0.50	1.00			
SMB D/E neutral	-0.49	0.95	1.00		
SMB DD neutral	-0.65	0.83	0.83	1.00	
WML	0.06	-0.27	-0.37	-0.20	1.00

Figure 30 - Correlations among explanatory variables

To evaluate the explanatory power of alternative SMB factors, equation (4) is estimated with the standard SMB and neutral SMB factors. The alphas and adjusted R^2 are reported in Figure 31. The GRS test statistics are also calculated as:

$$\text{GRS statistic} = \frac{T(T-N-L)}{N(T-L-1)} * \frac{\hat{a}'\hat{\varepsilon}^{-1}\hat{a}}{1+\bar{\mu}'\hat{\Omega}^{-1}\bar{\mu}} \sim F(N, T-N-L)$$

T and L are numbers of observations and explanatory factors (thus T=515 and L=3). N is the number of tested portfolios (thus N=5 for five size-ranked portfolios and N=6 for six Size-M/B portfolios). $\hat{a}$ is a column vector of alphas and $\bar{\mu}$ is a 3 by 1 column vector of sample means for factors' returns. $\hat{\varepsilon}$ and $\hat{\Omega}$ are the residual covariance matrix and the factors' covariance matrix.

As displayed in Figure 31, when the risk proxy is the D/E, the explanatory power of SMB is slightly affected. For five size-ranked portfolios, the average absolute of alphas and GRS statistic decrease marginally. For six Size-M/B portfolios, the average absolute of alphas remains unchanged, while the GRS statistic increases by only 0.2.

However, there is a considerable change in the power of SMB if the DD measures distress risk. For both classes of tested portfolios, the average absolute of alphas rises, especially in six portfolios sorted on size and M/B, an increase of 40% is observed. Furthermore, the GRS statistic also escalates, from 1.5 to more than 2. For six Size-M/B portfolios, the GRS statistic (2.44) is higher than the critical value at the 5% level (2.21). Hence, regressions with the DD-neutral SMB do not completely describe stock returns, particularly small-cap shares. The estimated alpha of the small is substantially positive, at 15 basis points. The adjusted R^2 also drops considerably. For example, for the small-value portfolio, the adjusted R^2 of the original Fama-French regression is 0.76, while the adjusted R^2 of the regression with the DD-neutral SMB is only 0.6. In other words, the excess return on small stocks would not be captured if the SMB is formed with risk neutrality.

Panel A: Five size-ranked portfolios												
	Fama-French SMB				SMB D/E neutral				SMB DD neutral			
	a(%)	t(a)	Adj.R^2	DW	a(%)	t(a)	Adj.R^2	DW	a(%)	t(a)	Adj.R^2	DW
1-Big	0.03	0.77	0.93	2.12	0.02	0.51	0.93	2.15	0.01	0.25	0.93	2.15
2	-0.09	-1.42	0.75	1.95	-0.08	-1.28	0.75	1.97	-0.04	-0.64	0.72	1.91
3	-0.03	-0.47	0.77	1.92	-0.02	-0.31	0.78	1.92	0.04	0.60	0.71	1.81
4	-0.05	-1.02	0.82	2.01	-0.03	-0.69	0.82	2.02	0.04	0.61	0.71	1.89
5-Small	0.06	1.08	0.77	2.02	0.08	1.40	0.77	1.97	0.15	2.24	0.70	1.87
Average absolute alpha (%)	0.051				0.045				0.055			
GRS test statistic	GRS = 1.51 (p-value = 0.18)				GRS = 1.38 (p-value = 0.23)				GRS = 2.09 (p-value = 0.06)			
Panel B: Six portfolios ranked on size and market-to-book												
	Fama-French SMB				SMB D/E neutral				SMB DD neutral			
	a(%)	t(a)	Adj.R^2	DW	a(%)	t(a)	Adj.R^2	DW	a(%)	t(a)	Adj.R^2	DW
Big-Growth	0.00	0.08	0.92	2.11	0.00	-0.08	0.92	2.13	-0.01	-0.23	0.92	2.15
Big-Neutral	0.09	1.14	0.69	1.94	0.08	1.06	0.69	1.95	0.08	1.13	0.69	1.94
Big-Value	-0.06	-0.85	0.80	2.06	-0.07	-0.92	0.80	2.07	-0.04	-0.54	0.80	2.02
Small-Growth	-0.04	-0.65	0.73	1.75	-0.02	-0.35	0.73	1.80	0.04	0.62	0.66	1.75
Small-Neutral	-0.02	-0.38	0.78	2.06	-0.01	-0.15	0.79	2.04	0.05	0.77	0.72	1.94
Small-Value	0.10	1.33	0.76	1.99	0.13	1.70	0.73	1.85	0.22	2.40	0.61	1.76
Average absolute alpha (%)	0.05				0.05				0.07			
GRS test statistic	GRS = 1.55 (p-value = 0.16)				GRS = 1.7 (p-value = 0.12)				GRS = 2.44 (p-value = 0.02)			

Note: The White robust standard errors are estimated to deal with the heteroscedasticity. DW is the Durbin-Watson statistic. Since DW statistics are close to 2, the autocorrelation is not an important issue in regressions. Adj.R^2 is the adjusted R^2. t() is the t-statistic.

Figure 31 - Summary of three-factor regressions

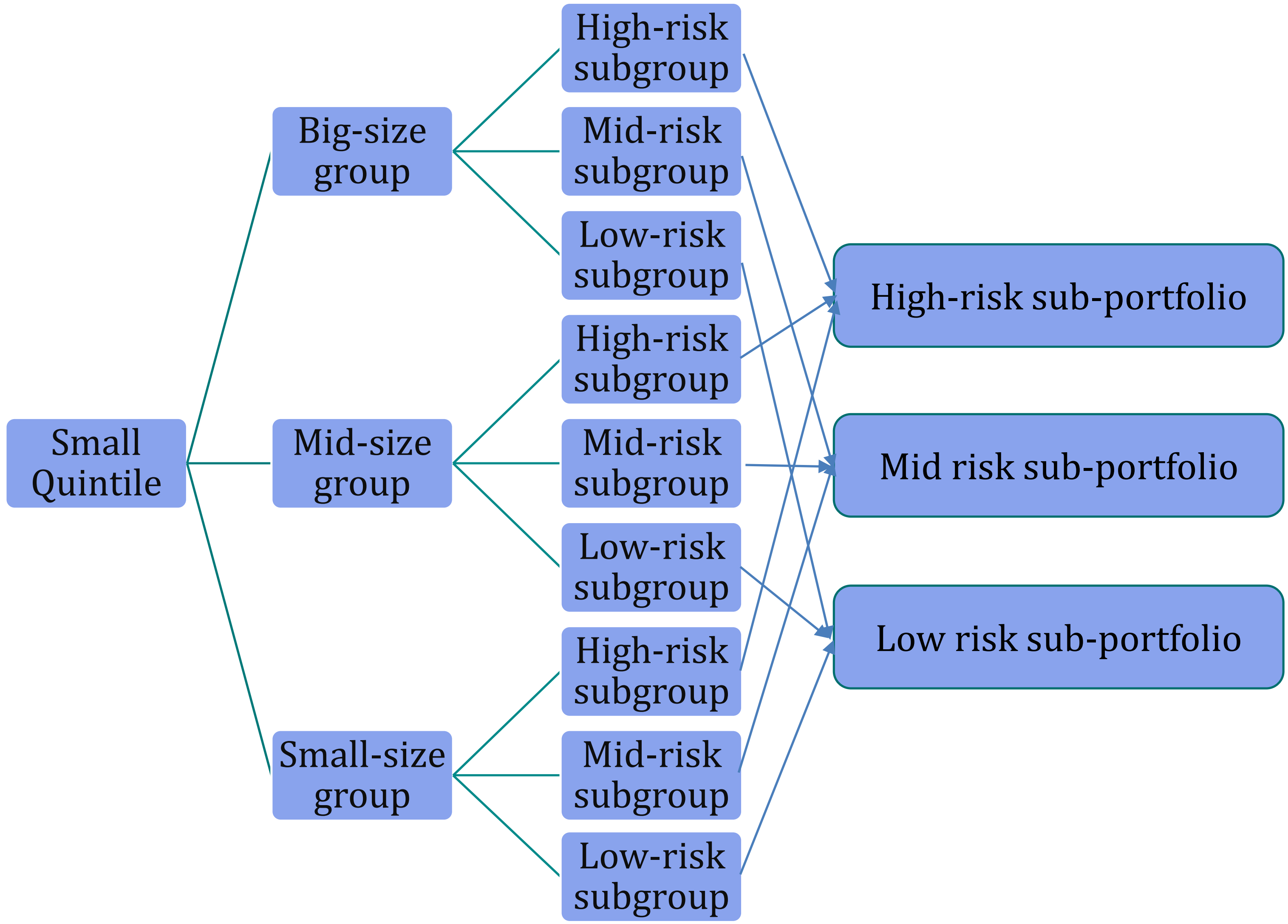

Figure 32 - An illustration of triple-sorted technique applied to the small quintile

Additionally, following Barillas and Shanken's (2017) framework, we also assess whether the neutral SMB factors are redundant by regressing SMB factors on the market and momentum factors. A significant regression alpha implies that the factor includes incremental information in expected returns (Barillas and Shanken, 2017). The D/E neutral SMB has a lower estimated alpha with a lower standard error than the Fama-French SMB (see Figure 33), which indicates that the amount of additional information in the SMB reduces when the D/E neutrality is imposed. Meanwhile, the alpha of DD neutral SMB is statistically insignificant with a t-statistic of only 1.07. Hence, the SMB with DD neutrality is likely to be a redundant factor.

To sum up, the explanatory power of SMB would be negatively affected if the default-risk neutrality is conducted. The D/E neutral SMB has slightly lower explanatory power than the standard SMB, while the DD neutral SMB seems irrelevant for stock returns. It corroborates the previous findings in section 6.4.2.

	Intercept (%)	R_m-R_f	WML	Adj. R^2	DW
SMB	0.14**	-0.27***	-0.26***	0.31	1.77
	(2.44)	(-9.66)	(-5.84)		
SMB D/E neutral	0.11*	-0.26***	-0.37***	0.35	1.85
	(2.08)	(-9.54)	(-8.09)		
SMB DD neutral	0.05	-0.35***	-0.17***	0.45	1.98
	(1.07)	(-13.5)	(-4.53)		

Note: The White robust standard errors are estimated to deal with the heteroscedasticity. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively. t-statistics are in parentheses. Adj.R^2 is the adjusted R^2

Figure 33 - Results of redundancy tests

6.6. Conclusion

As the size effect is reported in many developed and emerging stock markets, it becomes a well-known anomaly in the field of empirical finance. In spite of solid empirical proof supporting the size effect, the literature is inconclusive on the reason behind the excess returns of small stocks. While Fama and French (1996), Vassalou and Xing (2004), and Hwang et al. (2010) state that this superior return is compensation for distress risk; Dichev (1998), Campbell et al. (2008), Hur et al.

(2014), Groot and Huij (2018) find no relation between the size premium and default risk. This research contributes to extant studies in the following value-enhancing aspects.

Firstly, we re-examine the size effect in Vietnam, a dynamic frontier market in the CIVETS group. During 2009-2019, the smallest quintile generates the highest average return, at 19.34% per annum. Except for the biggest quintile, the lower the market capitalization, the higher the return.

Secondly, the link between the size effect and default risk is investigated in the Vietnamese context. Using the debt-to-equity ratio and distance-to-default of Merton (1974) as risk proxies, we document that excess returns on small shares are concentrated in stocks with high distress risk. In the small quintile, the annual mean returns on high-risk and low-risk sub-portfolios are approximately 36% and 9%, respectively, when the distance-to-default measures distress risk. Therefore, distress risk is subject to account for the size premium.

Finally, since among four Fama-French mimic factors, only the size factor (SMB) is not redundant in Vietnam (see section 4.5.2). This article assesses the explanatory power of the size factor with distress-risk neutrality. Empirical results show that for both risk proxies, the power of neutral SMB factors is negatively affected. There is a significant decrease in the average return of size factor when the default-risk neutrality is applied. The asset pricing model's performance reduces considerably when the distance-to-default neutral SMB replaces the standard SMB. Additionally, the distance-to-default neutral SMB includes no incremental information on expected returns according to the framework of Barillas and Shanken (2017).

Taken together, it could be concluded that default risk drives the size premium in Vietnam, which is consistent with a risk-based explanation. In other words, Vietnamese investors rationally charge a premium for holding small shares with higher default risk.

The findings of this chapter have several important implications for both academic researchers and investors. In the first place, the small-cap strategy is profitable, which implies that investors and fund managers might invest in the smallest stocks to generate abnormal returns in the Vietnamese equity market.

Furthermore, since the size premium is concentrated in stocks with high bankruptcy risk, investors should be well-equipped to realize firms with high default probability, then make plausible investment decisions based on the risk level.

7. Conclusion

7.1. Key findings

It is undeniable that the Efficient Market Hypothesis has played an important role in modern finance. Numerous studies have undertaken efforts to contest the argument of the Efficient Market Hypothesis and demonstrate the existence of stock market anomalies. Three important anomalies that challenge the market efficiency are the value/growth, momentum, and size effects. The literature predominantly focuses on developed markets such as the US, Europe, Japan, etc. Despite of the substantial six-fold growth in its capitalization in the last decade, the Vietnamese market has been mostly underrepresented in the academic literature. Research studies investigating this market are few and far between although Vietnam is one of the most dynamic markets in Asia and attracts massive attention of foreign investors. Therefore, the thesis aims to contribute to the extant literature by intensively examining the value/growth, momentum, and size effects in Vietnam, an important frontier emerging market. Several key findings are reported in this research as follows.

Firstly, there is solid proof of a growth effect in Vietnam, contrary to the value effect in developed markets. Investing in growth stocks leads to the highest average annual return, at more than 12.4% during 2009-2019. In seven out of ten sample years, growth stocks outperform value stocks. Since three out of four Fama-French mimic factors (the value, profitability, and investment factors) contain no incremental information on expected returns relative to the market and size factors, the CAPM and Fama-French multifactor models fail to give a resonable explanation to the growth effect in Vietnam. By contrast, a model including the market, size, and momentum factors succeeds to explain the growth effect. Because of high exposure to the momentum factor, the growth portfolio's superior return arises from the momentum effect. Furthermore, because the momentum factor provides positive profitability in only nine months after portfolio formation, the delayed overreaction is likely to be the key reason behind Vietnam's momentum effect. Most growth stocks are issued by big and highly profitable firms, which represent attractive investments. Hence, due to the presence of herd behavior, investors are inclined to overreact to the good news about their past stock returns, sending their stock prices to unduly high levels. It is the key reason why growth stocks outperform the others.

Secondly, motivated by models of Daniel et al. (1998) and Byun et al. (2016), we build a measure of overreaction in Vietnam based on trading volume and the sign of stock returns. A combination of high trading volume and positive (negative) return implies overreaction to positive (negative) private information, pushing their prices above (below) their long-term values. Since stocks that are faced with a stronger upward overreaction provide a higher average return, our measure of overreaction could be a predictor of Vietnamese stock returns. According to Daniel et al. (1998), if the level of overreaction remains unchanged, momentum does not exit. Therefore, to examine whether momentum exits after controlling for overreaction, we carefully make a comparison between trading strategies based on overreaction and price momentum strategies. The momentum profit disappears after controlling for the effect of overreaction, whereas the trading strategy based on overreaction provides significant returns even we adjust for the momentum effect. The overreaction trading strategy generates higher risk-adjusted returns than the momentum strategy within the framework of the CAPM and the Fama-French three-factor model. Furthermore, by double-sorting, we find that controlling for past returns, the average returns of portfolios rise monotonically with their measure of overreaction. On the other hand, there is no pattern in the average returns of portfolios sorted on past returns within each overreaction quintile. Given this backdrop, momentum in Vietnam is likely to arise from the investors' overreaction to private information as suggested by Daniel et al. (1998).

Finally, evidence of the size effect in Vietnam is documented over the sample period. By purchasing and holding the smallest stocks during 2009-2019, investors are able to earn a considerably high average return of 19.34% per year. Consequently, we examine whether default risk drives the size premium in Vietnam. The debt-to-equity ratio and distance-to-default of Merton (1974) are used as risk proxies. By triple-sorting stocks on their market capitalization and risk proxies, we document that excess returns on small shares are concentrated in stocks with high default risk. When distance-to-default is the risk proxy, the average return on small shares with high distress risk is more than 35% per annum, close to four times the average return on small low-risk shares. In addition, the explanatory power of size factor is evaluated when the default-risk neutrality is imposed. Adopting the technique suggested by Groot and Huij (2018), we create neutral size factors by initially ranking stocks on their risk proxies. These neutral size factors are built to dissect returns on the Fama-French size factor from the distress risk premium. Empirical results show that the explanatory power of size factor decreases when the default-risk neutrality is imposed. If distress risk is measured by the distance-to-deafult, the neutral size factor is likely to be an insignificant factor. Taken together, default risk is the key reason for the size effect in Vietnam, which is consistent with the risk-based explanation.

These findings lead to a couple of vital implications for investors and fund managers. The first implication is the existence of growth, momentum, and size effects in the Vietnamese stock market. Thus, investors might exploit these inefficiencies to earn superior returns in Vietnam. Secondly, since both growth and momentum effects arise from the investors' overreaction, our measure of overreaction could be used as a preditor of Vietnamese future stock returns. Meanwhile, because the size premium is concentrated in stocks with high default risk, investors should pay attention to the bankruptcy risk when investing in small shares.

7.2. Limitations and directions for further research

The empirical findings of this research are subject to several limitations in terms of data sample and methodology.

The first limitation is the disregard of transaction costs and income taxes. As presented in section 4.4.1, section 5.3.3, and section 6.4.1, investors do not hold stocks for the entire period. They revise and rebalance portfolios periodically, then transaction costs incur when buy and sell orders are executed. In fact, the transaction costs could be considerable, which reduces the portfolio' return significantly. Similarly, the income taxes on the stock dividends and capital gains may also have a great impact on the actual portfolio' return. In Vietname, transaction costs are commonly set at 0.15% while the income tax for investors is about 5% per year.

The second disadvantage is the sample size. Due to the availability of data and time limitation, only 10-year period is taken into account. The chosen market portfolio is also disadvantageous to some extent. In Vietnam, a great amount of fund is placed in the foreign currency (USD), bank deposits or financial derivatives. Thus, the market portfolio should consist not only the stock market index but also other financial assets.

Thirdly, in chapter 4, the stock market bubble is not taken into account. As shown in Figure 20, a bubble exists in the Vietnamese stock market between July 2017 and June 2018. Since the asset pricing models such as CAPM and multifactor models depend on historical data, stock market bubbles may lead to the inappropriate estimation of betas and factors' slopes.

In chapter 5, a combination of high trading volume and positive returns is considered as a proxy of overreaction to positive private information. However, it could be also viewed as a proxy of the disposition effect since investors may trade excessively due to being overconfident to their trading skills or enjoying the realization of capital gains. A precise distinction between the overconfidence trading and the disposition effect is somewhat subjective. A further survey study could be conducted to investigate how Vietnamese investors react to the good news about past stock returns.

Finally, in chapter 6, it would be better to collect credit ratings and spread credit for all sample stocks. Hence, by comparing empirical resuts for different default-risk proxies, the conclusion could be drawn more accurately. Furthermore, in addition to simultaneously solving two equations (see section 6.3.2), the distance-to-default could be also calculated using iterative estimation (Vassalou and Xing, 2004; Bharath and Shumway, 2008; Duffie et al., 2007; Aretz and Pope, 2013). Thanks to using different methods, computation of the default probability could be more precise.

As a result, a number of directions for further studies in Vietnam should be noticed. Firstly, the transaction costs and taxes should be incorporated in the return' computation. The price bubble could be considered as a risk factor in asset pricing models as suggested by Lee and Phillips (2016). Secondly, further theoretical development and empirical research on designed surveys may yield finer distinctions between overreaction and disposition effect in Vietnam. Finally, other explanations of the size effect such as liquidity risk or the January effet should be also examined in the Vietnamese stock market.

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Notes

[1]Livingston Survey is the oldest continuous survey of economists' expectations in the US, which summarizes the forecasts of economists from industry, government, banking, and academia. It is available from: https://www.philadelphiafed.org/surveys-and-data/real-time-data research/livingston-survey

[2]Durbin-Watson statistics for the monthly data interval are around 2.4, while Durbin-Watson statistics for the weekly data interval are close to 2.

[3]The growth quintile only outperforms the value in the first 9 months after portfolio formation (see Appendix A2)

[4]CIVETS countries are: Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa.

[5]Vassalou and Xing (2004); Groot and Huij (2018) sort stocks monthly, which leads to high transaction costs. As mentioned in chapter 4, ranking stocks twice a year seems to be more reasonable in Vietnam.

[6]The big portfolio generates a high return because of the momentum effect (see Appendix A4).

[7]According to the results of section 4.4.3, in Vietnam, the momentum factor with a pre-formation period of six months generates a higher average return than a pre-formation period of eleven months.

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Main abbreviations

AMEX: acronym for the American Stock Exchange

B/M: acronym for the book-to-market ratio

BRIC: acronym for Brazil, Russia, India, and China, used especially to refer to the fast-growing emerging economies.

CAPM: acronym for Capital Asset Pricing Model.

CMA: acronym for Conservative Minus Aggressive, which is considered as the investment factor in the asset pricing model developed by Fama and French (2016).

CPI: acronym for consumer price index, which could be used to measure inflation

CRSP: acronym for the Center for Research in Security Prices, a stock database in the US.

D/E: acronym for the debt-to-equity ratio

DD: acronym for the distance-to-default

EMH: acronym for the Efficient Market Hypothesis

ETF: acronym for exchange-traded fund

FF: acronym for Fama-French

FTSE All-share index: acronym for the market index published by the Financial Times newspaper. This index shows the price change of all stocks listed in the London Stock Exchange.

GDP: acronym for the gross domestic product

HML: acronym for High Minus Low, which is considered as the value factor in the asset pricing model developed by Fama and French (1996).

IBES: acronym for the Institutional Brokers' Estimate System

M/B: acronym for the market-to-book ratio

MSCI: acronym the Morgan Stanley Capital International

NYSE: acronym for the New York Stock Exchange

OR: acronym for overreaction, which is the measure of investors' overreaction as proposed in section 5.3.2.

P/E: acronym for the price-to-earnings ratio

RMW: acronym for Robust Minus Weak, which is considered as the profitability factor in the asset pricing model developed by Fama and French (2016).

SMB: acronym for Small Minus Big, which is considered as the size factor in the asset pricing model developed by Fama and French (1996).

STD: acronym for the standard deviation

WML: acronym for Winner Minus Loser, which is considered as the momentum factor in the asset pricing model developed by Fama and French (2012).

ANNEXES

A. Appendix A1

They are sorting the US shares into five quintiles on the M/B, Jaffe et al. (2020) report that, on average, 48.56% of stocks stay in the same quintile in the following year. If stocks are ranked annually in Vietnam, only approximately one-third of firms remain in a similar portfolio in the next year. Hence, Vietnamese firms tend to change their characteristic groups faster than US firms.

	1-Growth	2	3	4	5-Value	Entire sample
The US	60.75%	38.53%	33.90%	37.58%	62.49%	48.56%
Vietnam	57.072%	30.527%	24.266%	23.357%	41.226%	35.29%

Note: This table displays the percentage of shares in the same quintile in the next year. The US data is collected from Jaffe et al. (2020). The authors analyze the Vietnamese data.

Figure A1 - Proportions of sample in the same portfolio in the next year

B. Appendix A2

Following the same method of section 4.5.3.2, returns of growth and value quintiles are tracked in 24 months after portfolio formation. It is conspicuous that the growth only beats the value in the first 9 months. From month 10, the value quintile generates a higher return.

Months	1-3	4-6	7-9	10-12
Growth	2.354%	-0.449%	1.785%	-0.17%
Value	2.002%	-0.635%	1.504%	0.073%
Growth-Value	0.352%	0.186%	0.281%	-0.242%
Months	13-15	16-18	19-21	22-24
Growth	1.708%	-0.929%	1.807%	-0.46%
Value	1.769%	-0.162%	2.094%	0.36%
Growth-Value	-0.061%	-0.766%	-0.29%	-0.82%

Note: For the sake of brevity, the average returns every three months are reported.

Figure A2 - Returns on the growth and value quintiles following portfolio formation

C. Appendix A3

This appendix illustrates the calculation for benchmark-adjusted returns of momentum and overreaction portfolios in section 5.4.3. Assume that there are 15 different stocks that have equal capitalization in a sample period. Their returns are shown in Figure A3.

Stock	Return	Stock	Return
A	9.75%	I	7.23%
B	3.10%	J	5.18%
C	8.79%	K	4.79%
D	7.79%	L	4.19%
E	5.79%	M	7.42%
F	3.89%	N	3.32%
G	4.82%	P	3.16%
H	7.95%		

Figure A3 - Returns of 15 example stocks

Then, 15 example stocks are divided to five momentum portfolios based on the past returns during six months. Hence, each momentum portfolios includes three stocks. Since their capitalizaton are assumed to be equal, the raw return of each momentum portfolio is the equal-weighted average returns of three stocks. Similarly, 15 example stocks are independently grouped to five overreaction portfolios based on the estimated OR. Figure A4 displays the included stocks and raw returns of momentum and overreaction portfolios.

To estimate the benchmark-adjusted return for the winner portfolio, the return of each included stock is adjusted by the return of the overreaction decile where the stock belongs. To illustrate, based on the estimated OR, stock A is divided into portfolio 1, which has a return of 8.37%. Hence, its adjusted return is: 9.75% - 8.37% = 1.38%. Based on the estimaed OR, stock B is included in the third portfolio with a return of 4.93%. Consequently, the adjusted return of stock B is: 3.1% - 4.93% = -1.83%.

Similarly, the adjusted return of stock C is: 8.79% - 7.27% = 1.52%. Finally, the benchmark-adjusted return of the winner is: (1.38% - 1.83% + 1.52%) / 3 = 0.36%.

Panel A. Analysis on momentum portfolios					
	Winner	2	3	4	Loser
Included stocks	A, B, C	D, E, F	G, H, I	J, K, L	M, N, P
Raw returns	7.21%	5.82%	6.67%	4.72%	4.63%
Panel B. Analysis on overreaction portfolios					
Portfolios ranked on OR	1	2	3	4	5
Included stocks	A, H, M	C, E, I	D, B, F	J, K, P	G, L, N
Raw returns	8.37%	7.27%	4.93%	4.38%	4.11%

Figure A4 - Analysis on momentum and overreaction portfolios

The calculation of benchmark-adjusted return for portfolio 1 with the highest OR is shown as following:

Stock	Return	Momentum portfolio where stock belongs	Adjusted return
A	9.75%	Winner	9.75% - 7.21% = 2.54
H	7.95%	3	7.95% - 6.67% = 1.28%
M	7.42%	Loser	7.42% - 4.63% = 2.79%
Benchmark-adjusted return of portfolio 1			**2.2%**

Figure A5 - An example of calculation of benchmarrk-adjusted return

D. Appendix A4

The result of three-factor regressions with the market, size, and momentum factors is outlined in Figure A6. The test assets are five quintiles sorted on capitalization in section 6.4.1. Only the w coefficient of the big quintile is significantly positive, at 0.14, while w coefficients of other portfolios are approximately -0.4. Meanwhile, estimated betas for all quintiles are virtually equal, at around 0.9. The s coefficient rises monotonically from big to small portfolios. Thus, momentum is the reason why the big provides a higher return than the second, third, and fourth quintiles. Since most large firms are growth stocks, the explanation of returns on the big portfolio is similar to the growth portfolio presented in chapter 4.

$$R_{it} - R_{ft} = a_i + b_i * [R_{mt} - R_{ft}] + s_i * SMB_t + w_i * WML_t + \varepsilon_{it}$$

	a(%)	b	s	w	Adj. R^2	DW
1-Big	0.03 (0.77)	0.91*** (49.4)	-0.22*** (-7.29)	0.14*** (5.09)	0.93	2.11
2	-0.09 (-1.42)	0.89*** (26.1)	0.45*** (7.45)	-0.47*** (-10.0)	0.75	1.95
3	-0.03 (-0.48)	0.91*** (30.5)	0.66*** (13.5)	-0.41*** (-10.1)	0.77	1.92
4	-0.05 (-1.02)	0.9*** (33.9)	0.93*** (20.7)	-0.38*** (-10.1)	0.82	2.01
5-Small	0.06 (1.08)	0.93*** (30.0)	0.99*** (17.6)	-0.41*** (-9.85)	0.77	2.01

Note: The White robust standard errors are estimated to deal with heteroscedasticity. DW is the Durbin-Watson statistic. *, **, and *** imply the significance at 0.1, 0.05, and 0.01 respectively. t-statistics are in parentheses. Adj.R^2 is the adjusted R^2.

Figure A6 - Results of three-factor regressions on five size-ranked portfolios

E. Appendix A5

Following Merton (1974), the relationship between the assets volatility and equity volatility is proved as follows. Both the assets and equity are assumed to follow a geometric Brownian motion:

$$dV = \mu_V V dt + \sigma_V V dz$$

$$dE = \mu_E E dt + \sigma_E E dw \ (\mathbf{5})$$

Since E = F(V, t) as shown in equation (2) in section 6.3.2, from the Ito' lemma, we have:

$$dE = dF(V,t) = \frac{\partial F}{\partial t} dt + \frac{\partial F}{\partial V} dV + \frac{1}{2} * \frac{\partial^2 F}{\partial V^2} (\partial V)^2$$

$$= \frac{\partial F}{\partial t} dt + \frac{\partial F}{\partial V} (\mu_V V dt + \sigma_V V dz) + \frac{1}{2} * \frac{\partial^2 F}{\partial V^2} (\sigma_V V)^2 dt$$

$$= \left[\frac{\partial F}{\partial t} + \frac{\partial F}{\partial V} \mu_V V + \frac{1}{2} * \frac{\partial^2 F}{\partial V^2} (\sigma_V V)^2\right] dt + \frac{\partial F}{\partial V} \sigma_V V dz \ (\mathbf{6})$$

Setting like terms of (5) and (6) equal to each other, we have:

$$E\sigma_E = V \, \sigma_V \frac{\partial F}{\partial V} = V \, \sigma_V \frac{\partial E}{\partial V}$$

The $\frac{\partial E_0}{\partial V_0} = N(d_1)$ is proved as follows:

$$E_0 = V_0 . N(d_1) - e^{-r} . D . N(d_2)$$

$$d_1 = \frac{\ln\left(\frac{V_0}{D}\right) + \left(r + \frac{{\sigma_V}^2}{2}\right)}{\sigma_V}$$

$$d_2 = d_1 - \sigma_V$$

$$N(d_1) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{d_1} e^{\frac{-x^2}{2}} dx \text{ and } N(d_2) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{d_2} e^{\frac{-x^2}{2}} dx$$

According to the fundamental theorem of Lebiniz and $\lim_{x \to -\infty} e^{\frac{-x^2}{2}} = 0$, then we have

$$\frac{\partial N(d_1)}{\partial d_1} = \frac{1}{\sqrt{2\pi}} e^{\frac{-d_1^2}{2}} \text{ and } \frac{\partial N(d_2)}{\partial d_2} = \frac{1}{\sqrt{2\pi}} e^{\frac{-d_2^2}{2}}$$

$$\frac{\partial d_1}{\partial V_0} = \frac{1}{V_0 \sigma_V} \text{ and } \frac{\partial d_2}{\partial V_0} = \frac{1}{V_0 \sigma_V}$$

Then, we have:

$$\frac{\partial E_0}{\partial V_0} = N(d_1) + V_0.\frac{\partial N(d_1)}{\partial V_0} - e^{-r}.D.\frac{\partial N(d_2)}{\partial V_0}$$

$$= N(d_1) + V_0.\frac{\partial N(d_1)}{\partial d_1}.\frac{\partial d_1}{\partial V_0} - e^{-r}.D\frac{\partial N(d_2)}{\partial d_2}.\frac{\partial d_2}{\partial V_0}$$

$$= N(d_1) + V_0.\frac{1}{\sqrt{2\pi}} e^{\frac{-d_1^2}{2}}.\frac{1}{V_0 \sigma_V} - e^{-r}.D.\frac{1}{\sqrt{2\pi}} e^{\frac{-d_2^2}{2}}.\frac{1}{V_0 \sigma_V}$$

$$= N(d_1) + \frac{1}{\sqrt{2\pi}}.\frac{1}{\sigma_V}.e^{\frac{-d_1^2}{2}}\left[1 - e^{-r}.\frac{D}{V_0}.e^{\frac{d_1^2 - d_2^2}{2}}\right]$$

Then we need to prove that: $e^{-r}.\frac{D}{V_0}.e^{\frac{d_1^2-d_2^2}{2}} = 1$

In fact, d_1 and d_2 can be considered as (a+b) and (a-b), with: $a = \frac{\ln\left(\frac{V_0}{D}\right)+r}{\sigma_V}$ and $b = \frac{\sigma_V}{2}$. As $(a+b)^2 - (a-b)^2 = 4ab$, we have:

$$d_1^2 - d_2^2 = 4.\frac{\left[\ln\left(\frac{V_0}{D}\right) + r\right]\sigma_V}{2\sigma_V} = 2\left(\ln\left(\frac{V_0}{D}\right) + r\right)$$

Then: $e^{\frac{d_1^2-d_2^2}{2}} = e^{\ln\left(\frac{V_0}{D}\right)+r} = \frac{V_0}{D}.e^r \Rightarrow e^{-r}.\frac{D}{V_0}.e^{\frac{d_1^2-d_2^2}{2}} = e^{-r}.\frac{D}{V_0}.\frac{V_0}{D}.e^r = 1$