# “Empirical Essays on Stock Liquidity and Stock Return”

by

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Submitted in fulfilment of the requirement for the degree of Doctor of Philosophy (PhD) in Business

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March, 2021

## Acknowledgements

I would like to express my deep appreciation to my Supervisor, Professor Andros Gregoriou, for his continual support during my PhD studies, and his professional advice regarding my future career footpaths. Without his honest interest and motivation about my work this thesis would not be possible. I also thank my second supervisor, Dr Jerome Healy for his guidance.

In addition, I am very grateful to my friend, Dr Sijia Zhang who provided extremely valuable experience while pursuing my PhD degree. Furthermore, I express my gratitude to Brighton Business School of the University of Brighton for providing support for my doctoral studies and for being a pleasant environment to live, work, and study.

Finally, I would like to thank my husband, Tung Nguyen, and my child, Mai Anh Nguyen for their patience and unwavering support throughout my studies. I especially thank my husband for his willingness to listen to me ramble on about every aspect of my research and for his willingness to meticulously read through my thesis to offer sound grammatical advice. I also would like to express my appreciation to my parents and my whole family for their support.

Any shortcomings of this work are my sole responsibility.

## Abstract

This thesis provides a literature review of liquidity measures and empirical evidence of stock liquidity and stock return in the US stock market. Chapter 2 provides an extensive review of the literature on liquidity measures. Specifically, this chapter re-evaluates the existing liquidity measures with a primary focus on low-frequency measures, strengths, weaknesses, and their implications on asset pricing. The first empirical chapter tests the relationship between stock liquidity and asset pricing, using a new price impact ratio adjusted for the free float factor as an approximation of liquidity. The free float adjusted ratio is free from size bias and encapsulates the impact of trading frequency. It is more comprehensive than alternative price impact ratios because it incorporates the shares available to the public for trading. Using a data sample of all US listed companies over the time period of 1997-2017, this chapter provides evidence that the free float adjusted price impact ratio is superior to other price impact ratios used in the previous academic literature. I also discover that the chapter's findings are robust to the financial crises between 2007-2009.

The second empirical chapter examines the joint effect of advertising intensity and product market competition on stock returns. Using a sample of the US market over the period from 1977 to 2018, I provide evidence that advertising is negatively associated with stock returns, and this correlation is stronger for firms in competitive industries. In addition, higher expected stock returns are seen in firms in competitive markets, compared to firms in concentrated industries, especially among low advertising intensity groups. My results are robust across alternative subsamples and product market competition measures. My empirical estimates support the positive causal effect of concentration on advertising.

The third empirical chapter studies the effect of corporate social responsibility (CSR) on stock performance in the face of hurricane strikes. Using a sample of non-financial public US firms between 1992 and 2012, I find a positive correlation between CSR engagement and stock

return of hurricane-afflicted firms. I also provide evidence that stock liquidity measured by trading volume and the Amihud ratio is positively associated with CSR through hurricanes. Furthermore, these effects are mainly because of investing in external CSR categories, including Community, Human Rights, and Environment, on a long time basis. However, my results suggest that the positive impact of CSR and stock performance are induced through hurricane occurrence only. Overall, this thesis's findings contribute to the literature on stock liquidity and stock return by testing a new liquidity measure and new determinants of stock liquidity and stock return. This thesis also has important insights for academic research and professional practice. First, it provides evidence about a more comprehensive liquidity ratio, namely the free float adjusted price impact ratio. This measure is shown to be a more accurate approximation of stock liquidity. Moreover, the thesis suggests that advertising is negatively associated with stock return. As a result, firms should consider carefully before investing in advertising campaigns. Finally, the last empirical chapter about CSR indicates the insurance-like effects of CSR engagement on stock performance. It has important implications for the insurance policies of firms for a long time.

## Declaration of Originality

*"I hereby declare that this thesis and the work to which it refers are the results of my own efforts. The work, of which this is a record, has been carried out by myself unless otherwise stated and where the work is mine, it reflects personal views and values Any ideas, data, images or text resulting from the work of others (whether published or unpublished) are fully identified as such within the work and attributed to their originator in the text, bibliography or in footnotes. This thesis has not been submitted in whole or in part for any other academic degree or professional qualification. As of submission date, a paper based in Chapter 2 of this thesis has been published in the Journal of Economic Survey as an article entitled "How do you capture liquidity? A review of the literature on low- frequency stock liquidity" co-authored with Andros Gregoriou.*

*Le, Huong and Gregoriou, Andros 2020. How do you capture liquidity? A review of the literature on low- frequency stock liquidity, Journal of Economic Survey 34, 1170-1186."*

Thi Thu Huong Le, March 2021

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# CHAPTER 1: INTRODUCTION

Stock liquidity is a fundamental component of financial markets and academic research, thus stock liquidity and related issues are becoming one of the primary streams of the finance literature. It has not only been of interest to researchers, but it also concerns investors across the globe. Liquidity is considered as a key attribute of capital assets and highly impacts their prices (Amihud and Mendelson, 1991). Liquid stocks are defined as stocks which are able to trade large volume quickly at low cost with little price impact. According to this definition, stock liquidity is reflected in four dimensions, including trading quantity (how much security can be traded at a given cost), trading speed (how quickly can security be traded at a given cost with given quantity), trading costs (all expenses related to the trade of a given quantity of security), and price impact (how easy it is to trade security of a given quantity with minimum impact on price, Liu, 2006). Due to the importance of stock liquidity, a large body of prior papers focus on liquidity measures, whereas others seek the factors that affect stock liquidity.

Stock return is also an important stream of academic literature. The question of which factors drive stock returns has prompted vast amounts of research and is still one of finance's main challenges. The first model of stock returns is the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965). According to the CAPM, an asset's expected return is a linear increasing function of its market risk or market beta. However, empirical evidence has shown that this model fails to explain the size and book-to-market effect (Rosenberg, Raid, and Lanstein, 1985; Fama and French, 1992, 1993). Fama and French (1993) introduce the three-factor CAPM model, which captures the effect of size and book-to-market equity on stock return. In particular, the size factor is the return of three portfolios of small stocks minus the return of three portfolios of big stocks with the same weighted-average book-to-market equity. The book-to-market factor is the difference between the return of two high book-to-market equity portfolios and two low book-to-market equity portfolios. Fama and

French (1996) argue that the Fama and French three-factor model absorb most of the anomalies that plagued the CAPM. Carhart (1997) incorporates a momentum risk factor, whereas Fama and French (2015) include profitability and investment factors in the three-factor model. Other factors are also found to have explanatory power, including firm size (Reinganum, 1981) and dividend yields (Litzenberger and Ramaswamy, 1979). Recently, Gregoriou et al. (2019) develop a seven-factor model that is based on the Peak-End rule of Fredrickson and Kahneman (1993) from Prospect Theory (Kahneman and Tversky, 1979, 1992). They provide evidence that the new model is more comprehensive in explaining variations in asset returns.

Although researchers widely investigate stock liquidity and stock return, there are still concerns related to the liquidity measures and factors affecting the variation of stock liquidity and stock return. For this reason, my thesis aims to further explore this issue by providing empirical evidence on a new liquidity measure. In addition, I will examine how some corporate and exogenous factors impact the relationship between stock liquidity and stock return using data from the US stock exchange.

**Chapter 2** provides a review of the literature concerning low-frequency liquidity measures, stock return, and existing asset pricing models. Liquidity and related issues have a crucial role for both economics and practitioners, thus receiving considerable attention in the literature. Several liquidity measures are introduced to measure stock liquidity, which capture one or more dimensions of liquidity. Due to the importance of liquidity, it requires a better understanding of liquidity measurement and the merits and demerits of existing liquidity measures. Therefore, this chapter aims to give an extensive review to re-evaluate the existing liquidity measures with a primary focus on low-frequency measures, pros and cons, and their implications on asset pricing. Specifically, I not only focus on well-known measures such as trading volume and the Amihud (2002) illiquidity ratio, I also examine recently proposed measures such as the new spread of Abdi and Ranaldo (2017), the Florackis, Gregoriou, and

Kostakis (2011) return to turnover ratio and the Karim, Azevedo, Gregoriou, and Rhodes (2016) free float adjusted price impact ratio. This chapter is one of the primary studies which provides a comprehensive and up-to-date literature review of low-frequency liquidity measure. Besides, I also review the literature on stock return and existing widely used asset pricing models. The first asset pricing model is known as the CAPM proposed by Sharpe (1964) and Lintner (1965), independently. This model provides an insight into the kind of risk correlated to stock return with the idea that asset prices may not reflect all related risks. Unfortunately, empirical studies have shown that the CAPM fails to predict expected returns of assets. Being motivated by that, further multi-factor models have been introduced to capture the effect of risk on stock return. This chapter focuses only on widely used asset pricing models, including the CAPM, the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and the five-factor model of Fama and French (2015). These models are also used in my thesis when considering asset prices.

**Chapter 3** examines the empirical relationship between stock liquidity and stock returns using a new liquidity measure. The growing interest in liquidity and its impact on financial markets has resulted in establishing several liquidity measures by academic scholars. These measures capture different liquidity dimensions, including trading quantity, cost, speed, and price impact. One of the most widely used liquidity proxies is the Amihud illiquidity ratio (hereby RtoV ratio), known in the literature as the return to volume ratio (Amihud, 2002). It reflects the change of security prices when a number of stocks are traded. However, the return to volume ratio exhibits a firm size bias as there is a solid positive relationship between trading volume and the firm's market capitalization. It also fails to reflect the trading frequency aspect of stock liquidity. An alternative price impact ratio is proposed by Florackis, Gregoriou, and Kostakis (2011), namely, the return to turnover ratio (hereby RtoTR ratio), which is defined as the ratio of daily absolute stock return to turnover. Employing turnover in calculating liquidity measures allows the RtoTR ratio to control both the effect of trading costs and trading frequency on asset pricing.

Nevertheless, there is an issue with both the RtoV and RtoTR ratios, which has not been mentioned in the Florackis, Gregoriou, and Kostakis (2011) study. The problem is that the number of shares outstanding used in constructing these liquidity proxies does not reflect the real number of available stocks that are accessible to the public for trading. Lam, Lin, and Michayluk (2011) argue that the number of available shares (public free float factor) affects stock liquidity level as the higher supply of the stock makes it easier to trade. Hence, they suggest that a liquidity measure should consider the supply ability of stocks in predicting trading costs. In this chapter, I aim to test the efficiency of a new price impact ratio – the free float adjusted price impact ratio introduced by Karim et al. (2016). This new liquidity measure replaces the turnover ratio in the denominator component of the RtoTR ratio by adjusted turnover ratio controlling for the public free float factor. The adjusted turnover ratio increases the encapsulation power of price impact, which is defined as the ability of the ratio to approximately capture the cross-sectional variability turnover ratio of the security. The free float adjusted price impact ratio (hereby RtoTRF ratio) inherits the benefits of the RtoTR ratio and has additional appealing features.

Using the stock data of all public firms listed in three main stock exchanges of the US market (NYSE, AMEX and NASDAQ), this chapter finds a positive relationship between average stock return and the level of RtoV ratio. However, a puzzling result is that a decrease in the liquidity level leads to a decline in stock returns when using the RtoTR and RtoTRF ratios as liquidity measures. In particular, more liquid stocks (low RtoTR or RtoTRF price impact ratios) yield higher returns than less liquid stocks. In addition, using the time-series tests, I discover that risk-adjusted return of portfolios constructed on the basis of the RtoTRF ratio is higher than the returns of portfolios sorted based on the RtoTR ratio. This suggests that the free float adjusted price impact ratio has superior performance than the RtoTR ratio in the US market.

This chapter contributes to the previous literature in the following ways. It is the first study to provide empirical US evidence on the influence of liquidity on asset prices using the free float adjusted price impact ratio introduced by Karim et al. (2016) as a liquidity proxy. This chapter also adds to the literature in understanding the explanatory power of the most commonly used asset pricing models by academics and practitioners through analysing the context of multiple forms of asset pricing frameworks.

**Chapter 4** examines the interaction impact of product market competition and advertising on stock returns. Advertising plays a crucial role in increasing differentiation and awareness of a firm in a competitive business environment. However, previous studies do not account for the effect of competition in the given product market and the influence of advertising on industry concentration and returns. This chapter studies the joint impact of product market competition and advertising intensity on stock returns using portfolio sorts, the CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama-French (2015) five-factor model technique. Particularly, a conventional double-sorting approach is employed to test the interaction effect between advertising and the competitive degree of industries on expected stock returns.

Following previous research, this chapter focuses on advertising intensity, expressed as the ratio of advertising expenditures on sales revenue rather than the level of spending on advertising (see, for example, Lou, 2014 and Vitorino, 2014). This chapter finds evidence that higher advertising intensity is associated with lower expected stock returns, and this negative relation is stronger for firms in more competitive industries. The tests show that the negative relationship between advertising and stock returns exists only in competitive industries. These findings hold across all asset pricing models, including the CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama-French (2015) five-factor model. I also report a positive relation between product market competition and stock returns and this association exists only among low advertising intensity groups. Specifically, firms with a low ratio of advertising to sales revenue experience a monotonic increase in the portfolio raw returns and abnormal returns following the competitive degree. These results are robust when using different breakpoints and asset pricing models.

This chapter contributes to the past research studying the relationship between advertising and stock return by showing how firms' competitive degree in a given industry can affect this association. This chapter also contributes to the literature concerning the association between product market competition and stock returns.

**Chapter 5** investigates the effect of corporate social responsibility (CSR) on stock performance, including stock liquidity and stock return following a hurricane strike. Natural disasters like hurricanes not only cause economic losses and fatalities but also disrupt the corporate operation, affect business conditions which have impacts on firms' performance. Prior research extensively studies the impact of a hurricane on a firm's performance (Dessaint and Matray, 2017; Aretz, Banerjee, and Pryshchepa, 2018; Kruttli, Tran, and Watugala, 2019). The increase in extreme weather and climate events has put the stakeholders' interests under public attention, motivating academic and managerial interest in CSR investment. On the one hand, CSR is believed to add to firm value by positively shaping stakeholder perceptions (Deng, Kang, and Low, 2013). On the other hand, CSR is argued to be correlated with agency problems and incentive issues (Jensen, 2002). Due to the increase in the importance of CSR, this chapter examines whether CSR activities can protect firms against the negative exogenous shocks caused by hurricanes. In particular, I study how stock return and liquidity respond to hurricane strikes when firms are located in the neighborhood of the disaster areas and test the insurance-like effects of CSR in the face of exogenous shocks like hurricanes.

Using different stock liquidity measures, this chapter finds a positive effect of engaging in CSR on the stock liquidity of hurricane-affected firms. In addition, I also show that CSR engagement is positively associated with abnormal returns of firms in hurricane-afflicted areas. This finding holds when I employ different CSR measures and control for corporate governance.

This chapter's contribution is that it adds value to the strand of literature that studies the impact of hurricanes on a firm's activities. My chapter provides evidence for economic losses caused by hurricane landfalls by presenting the adverse effects of these disasters on shareholder value. I also show that after the hurricane event, stocks are more liquid and exhibit higher returns. Moreover, the chapter indicates the insurance-like effects of CSR activities on hurricane-affected firms.

Overall, each empirical chapter's results highlight the relationship of different factors on the association between stock liquidity and stock return. These chapters contribute to the literature studying the factors which drive stock liquidity and stock return.

The remainder of the thesis is structured as follows: Chapter 2 provides relevant literature relating to stock liquidity and stock return. Chapter 3 empirically examines the relationship between stock liquidity and asset pricing using a new price impact ratio as a liquidity measure. Chapter 4 tests the joint effect of advertising intensity and product market competition on stock returns. Chapter 5 investigates the effect of CSR on stock performance under the occurrence of hurricane strikes. Finally, Chapter 6 offers final remarks and conclusions from this thesis.

# CHAPTER 2: LITERATURE REVIEW ON STOCK LIQUIDITY AND STOCK RETURN

This literature review summarizes relevant studies relating to stock liquidity and stock return. While each study cited in this review may not play an integral part in the empirical research of this thesis, this body of research provides the backdrop and colors the motivation behind this thesis. Additionally, each empirical chapter in this thesis touches upon the literature relevant to that specific study.

This chapter is presented as follows: Section 2.1 provides relevant literature on the subject of stock liquidity and liquidity measures. Section 2.2 reviews literature regarding asset pricing models and stock return. Finally, section 2.3 concludes the chapter.

## 2.1 Stock liquidity and liquidity measures

Liquidity and associated issues are one of the primary streams of the finance literature, which receive considerable attention from researchers. Over the last four decades, numerous studies are focusing on this area, such as Amihud and Mendelson (1986a), Eleswarapu and Reingarnum (1993), Vayanos (1998), and Chordia, Subrahmanyam, and Anshuman (2001). Several important works are Amihud (2002), Vayanos (2004), Acharya and Pedersen (2005), Amihud, Mendelson, and Pedersen (2005), and Hasbrouck (2009). In spite of abundant theoretical and empirical literature on liquidity and related issues, there is not an appropriate definition of liquidity as well as a consistent liquidity measure for all markets. This is because the liquidity concept contains some dimensions, including the quantity of trade, trading time, and price impact. One of the most accepted descriptions of liquidity comes from Liu (2006). In particular, liquid stocks are defined as stocks which are able to trade large volume quickly at low cost with little price impact. Four dimensions of stock liquidity can be seen from this definition, namely trading quantity (how much security can be traded at a given cost), trading speed (how quickly can security be traded at a given cost with given quantity), trading costs (all expenses related to the trade of a given quantity of security), and price impact (how easy it is to trade security of a given quantity with minimum impact on price). This definition reflects five characteristics of a liquidity asset: tightness, immediacy, depth, breadth and resiliency (see Black, 1971, and Sarr and Lybek, 2002). Similar definitions can be seen in Harris (2003) and Amihud and Mendelson (2012).

In addition, several measures are introduced and employed to calculate the liquidity of a security. Each measure captures one or more dimensions of stock liquidity. For example, the effective bid-ask spread measure of Roll (1984) implicit captures the transaction cost aspect of liquidity. On the other hand, the Amihud (2002) illiquidity ratio and Florackis, Gregoriou, and Kostakis (2011) return to turnover ratio are based on the price impact dimension. Furthermore, Liu (2006) presents a multiple dimension-based measure, namely turnover–adjusted number of zero daily trading volume. Although they focus on different aspects of liquidity, these measures are highly related to each other (see, e.g., Goyenko, Holden, and Trzcinka, 2009; and Fong, Holden, and Trzcinka, 2017).

Based on data frequency, liquidity proxies can be grouped into two strands, namely high frequency (intraday) and low frequency (daily) measures. High frequency liquidity measures are constructed from intraday data, whereas low frequency liquidity proxies are derived mainly from daily stock returns and volume data. High frequency liquidity proxies consist of intraday transactions, the data samples are usually very large and thus it requires advanced computer programming and power to analyze them. As a result, high frequency measures are mostly employed for US markets (see, e.g., Huang and Stoll, 1997; Hasbrouck, 2009). Overcoming these drawbacks, low frequency liquidity measures are widely used in application due to the following advantages. First, it is easy to access and available for not only large markets like the US and UK equity markets, but also for many other less established stock exchanges such as emerging markets. As a result, researchers can obtain the data across countries over long time periods, which enhances the research in the liquidity subject area. Moreover, these measures are very good at capturing the liquidity benchmarks based on intraday data. Indeed, Goyenko, Holden, and Trzcinka (2009) compare a wide range of low frequency liquidity measures with high frequency benchmarks and find a strong correlation between *Zeros* by Lesmond, Ogden, and Trzcinka (1999), return to volume ratio of Amihud (2002) and intraday benchmarks[1]. Together with some well-known measures such as the bid-ask spread, turnover, and the Amihud (2002) ratio, new measures are being constructed such as the Florackis, Gregoriou, and Kostakis (2011) price impact ratio, and the Karim et al. (2016) free float adjusted price impact ratio.

Despite these potential benefits, liquidity measures constructed from low frequency data exhibit some limitations. For instance, the Illiquidity ratio of Amihud (2002) is considered superior at capturing liquidity than most other measures (Fong et al., 2009) but it does not incorporate days without trading, which can contain important information about illiquidity. Furthermore, High-Low spread, which captures the transaction costs dimension of Corwin and Schultz (2012), is built under the assumption that the stock trades continuously while the market opens. This assumption is violated in practice, decreasing the accuracy of the High-Low spread. As a consequence, a more comprehensive understanding of existing liquidity measures is required for a better application.

Liquidity is considered as a key attribute of capital assets and highly impacts their prices (Amihud and Mendelson, 1991). Previous studies examine the relationship between liquidity and stock returns under two avenues. The first stream of research investigates if the level of liquidity as a characteristic influences expected returns of the security. When investing in

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1 *Zeros* is a liquidity measure proposed by Lesmond, Ogden, and Trzcinka (1999) using daily data. It captures the transaction cost dimension based on the frequency of zero return.

illiquid stocks, investors are compensated by higher stocks' return. Meanwhile, the other stream studies whether stock returns are affected by systematic liquidity risk. Liquidity is considered as a risk factor in asset pricing. The stock whose return is more sensitive to shocks in market liquidity has a higher expected return. Numerous studies provide evidence on the former relation to expected stock returns. For example, Amihud and Mendelson (1986a) show that liquidity cost (illiquidity) is positively correlated with expected asset returns when using the bid-ask spread as a liquidity proxy. Focusing on US equities, Brennan, Chordia, and Subrahmanyam (1998) also provide evidence that liquidity is negatively correlated with required asset returns when employing turnover ratio and trading volume, respectively, to measure liquidity. This relationship is also confirmed in emerging markets by Bekaert, Harvey, and Lundblad (2007). On the other hand, some empirical studies report conflicting evidence. Bekaert, Harvey, and Lundblad (2007) suggest that turnover does not significantly predict future return. Eleswarapu and Reinganum (1993) find evidence of seasonality by demonstrating that bid-ask spread and average returns are positively correlated to each other merely in January. Meanwhile, Hasbrouck (2009) proposes a new estimation of the trading effective cost from daily closing prices, and finds mixed evidence when examining the relationship between their cost measure and stock returns. In particular, they demonstrate that the effective cost has a positive association with stock returns, with the strongest relationship occurring in January.

The latter relation to stock returns is also widely examined in prior studies. For instance, Pástor and Stambaugh (2003) introduce a market-wide liquidity and show that expected returns of stock are correlated with the sensitivities of returns to fluctuations in aggregate liquidity. They find that the difference in average return of stock with high sensitivities to liquidity and that of low sensitive stock is 7.5% annually. Acharya and Pedersen (2005) show that liquidity is a priced factor in cross-section of stock returns. They introduce liquidity-adjusted Capital

Asset Pricing Model (CAPM) and argue that it is better than the standard CAPM. Other papers in this line of research are Hasbrouck (2009), Korajczyk and Sadka (2008), and Ben-Rephael, Kadan, and Wohl (2015).

Due to the crucial role of liquidity for both economists and practitioners, it requires a better understanding of liquidity measurement as well as the advantages and disadvantages of existing liquidity measures. Therefore, this chapter aims to provide an extensive review of the literature to re-evaluate the existing liquidity measures with primary focus on low frequency measures, merits, demerits and its implications on asset pricing.

In particular, the chapter focuses on a range of well-known low frequency liquidity proxies in different dimensions. Following Sarr and Lybek (2002), Liu (2006), I separate liquidity measures into four categories based on the dimension it captures, including transaction cost, volume based, price impact and multi-dimension based measures. Existing measures typically focus on one particular dimension of liquidity. For instance, the bid-ask spread captures the trading cost dimension, whereas the illiquidity ratio of Amihud (2002) relates to the price impact dimension. Together with some widely used liquidity measures, recently proposed measures such as the new spread estimate of Abdi and Ranaldo (2017), Florackis, Gregoriou, and Kostakis (2011) return to turnover ratio, and Karim et al. (2016) free float adjusted price impact ratio, are also considered in this chapter. In particular, I review prior research in both the US and other international financial markets. Due to a wide range of liquidity proxies, I am not able to review all of them. Therefore, I focus my attention on some widely used measures of each liquidity dimension. This chapter contributes to the literature concerning liquidity measures by providing a comprehensive and up-to-date review on low frequency liquidity proxies. This chapter considers not only well-known liquidity proxies but also some recently proposed measures of liquidity. Moreover, I also discuss any potential issues in using low frequency liquidity measures.

In summary, this chapter shows that each low frequency liquidity measure usually comes with both advantages and disadvantages. For instance, some proxies such as the High-Low spread of Corwin and Schultz (2012) and the Closing Percent Quoted Spread of Chung and Zhang (2014) are good at estimating bid-ask spread, but they are not able to encapsulate long run financial stability. As a result of this, subsequent proposed approximations of liquidity attempt to improve the shortcomings of previous measures. Unlike Corwin and Schultz (2012), the AR spread of Abdi and Ranaldo (2017) provides an adjustment for non-trading periods, and it does not rely on bid-ask bounces to capture the effective spread like Roll (1984). In addition, the Free float adjusted price impact ratio of Karim et al. (2016) captures the public free float factor, which increases the predictive power of price impact, compared to existing price impact ratios such as the Illiquidity ratio of Amihud (2002). Due to the data availability and simplicity, low frequency measures of liquidity are widely used in research and practice. However, some limitations remain compared to high frequency liquidity measures which are computed from intraday data. Thus, researchers are still seeking the best low frequency liquidity measure.

### *2.1.1 Transaction Cost based Measures*

Transaction costs refer to the expenses associated with the execution of a trade. Trading costs can be separated into two main categories, namely explicit and implicit costs. Explicit costs such as order processing costs, taxes, and brokerage fees are identifiable and known in advance of trading. Meanwhile, implicit costs are less observable, compared to explicit costs but can account for a large fraction of total transaction costs. Examples of components to implicit costs are bid-ask spreads, size of the transaction, and timing of trade execution.

Following Marshall, Nguyen, and Visaltanachoti (2012), spread is considered as the best transaction costs benchmark. Spread captures the transaction costs at the best bid and ask prices, and this cost is for the amount of security executed at the best bid and ask quote. Depth is also important to investors, which provides information about the amount that can be traded at a given price. When a trader needs to transact an order with the quantity being larger than the quantity of the best limit orders, the remaining portion may be filled at the second best bid or ask price. The difference in these executed prices and the traded quantities of stock at each price have impacts on transaction costs. Extant literature on market microstructure also shows that the bid-ask spreads are the most commonly used measure of trading costs as they capture nearly all of the costs associated with stock trading (Sarr and Lybek, 2002). Bid-ask spreads consist of three components, including order processing, information asymmetry, and the inventory cost components. Ever since the late 1960's, spread components and their behaviour are widely discussed by researchers in both theoretical and empirical literature (see, e.g., Demsetz, 1968; Stoll, 1978; Easley and O'Hara, 1987; Huang and Stoll, 1997; and Gregoriou, 2013).

Market makers or dealers are also considered as liquidity suppliers who provide immediacy of trade execution to the market by matching buy and sell orders (Demsetz, 1968). When order processing costs are high, dealers need to be compensated for this cost by posting relatively high bid and low ask prices. Meanwhile, inventory cost models claim that dealers in security markets may face risk when holding security as inventory due to the uncertainty about future returns as well as the time taken for the transaction to be executed (Ho and Stoll, 1981). In particular, unexpected changes in future stock price and market environment can lead to a potential loss for market makers. Another component of the bid-ask spread is asymmetric information. It happens when one party of a transaction has information about the true value of a security, whereas the other party does not. The informed party is more likely to trade with a larger quantity at any security price. Hence, market makers may face a potential loss when trading with investors who have private information due to the change in security's price. Moreover, it is uncertain about who the informed trader is and when an information event exists. As a result, dealers can increase the bid-ask spread to compensate for this potential loss when quoting the bid and ask prices.

High frequency forms of bid-ask spread include quoted bid-ask spread, relative bid-ask spread, and effective bid-ask spread. The quoted bid-ask spread is a straightforward proxy of illiquidity as it captures the transaction cost dimension. The quoted spread measures the cost of completing a round trip (buy and sell) if trades are executed at the quoted prices (Bessembinder and Venkateraman, 2010). Another form of spread is the relative bid-ask spread. It is defined as the dollar bid-ask spread over the midpoint of the closing bid and ask prices for the trading day. It overcomes the issue of quoted bid-ask spread being wider for large price stocks. This leads to a bias conclusion that large stocks are more illiquid than small securities. The effective bid-ask spread is devised to capture trading costs when they occur within the ask and bid prices in a more efficient manner. It is defined as twice the absolute value of the subtraction between a transaction price and the midpoint of bid and ask quotes at the time of the transaction. Although bid-ask spreads have some advantages in measuring liquidity and are widely employed in research, they also have their shortcomings. The limit in obtaining trade and quote data in all stock markets as well as a tedious process of data to calculate high frequency bid-ask spreads, raises the demand for alternative spread estimators. As a result, considerable emphasis has been placed on researching and proposing estimators of bid-ask spread, which are based on low frequency data. In this section, I review the construction as well as the advantages and disadvantages of some widely used estimators of bid-ask spreads. These include the Roll (1984) implicit effective spread, *Zeros* by Lesmond, Ogden, and Trzcinka (1999), High-Low spread of Corwin and Schultz (2012), Closing Percent Quoted Spread of Chung and Zhang (2014), and most recently spread measure of Abdi and Ranaldo (2017).

#### *2.1.1.1 Roll (1984) implicit effective spread*

Roll (1984) introduces an implicit spread based on the autocorrelation between bid and ask prices as a proxy of stock liquidity. The implied spread is defined as:

$$Roll_i = 2\sqrt{-\,cov_i} \tag{2.1}$$

Where $Roll_i$ is the implicit spread of stock i, $cov_i$ is the first order serial covariance of returns for stock i. The Roll estimator can be calculated using both daily and weekly data.

As noted by Roll (1984) under assumptions of an efficient market where relevant information is reflected quickly and accurately on prices, the quoted spread is constant and the average of bid-ask prices fluctuates randomly. The quoted bid-ask spread fails to capture the true transaction costs as most trades are executed within the bid and ask prices. These things motivate Roll (1984) to use the serial correlation of price changes to propose implicit spread as a proxy for liquidity. He also discovers that his proxy is strongly correlated to firm size, thus it supports the argument that the implicit spread captures the transaction cost dimension. It is argued that implicit effective spread can be obtained easily as it only requires transaction price data without information about the bid-ask spread and order flow. Other studies employ implicit effective spread as a proxy for liquidity, see for instance, Lesmond (2005), Fong, Holden, and Trzcinka (2017).

Nevertheless, the implicit effective spread is undefined if serial covariance is positive. Reinganum (1990) shows that forty-one percent of the security serial covariance are positive. To deal with this issue, Roll (1984) suggests that the sign of covariance is preserved after taking the square root, but the implicit effective spread will be recorded as a negative number. Meanwhile, Hasbrouck (2009) sets the spread equal to zero if the serial covariance is positive. Another problem is that for days with no trade, the midpoint of the closing bid and ask prices is still reported by the stock exchange. It leads to a bias in the estimated trading expense as the midpoint realizations do not contain the cost (Hasbrouck, 2009).

The Roll (1984) model is the first model which employs price data to estimate the effective spread. Since then, several models have been introduced. For example, Lesmond, Ogden, and Trzcinka (1999) propose a model to estimate transaction costs using daily security returns only. Compared with Roll (1984), they introduce an estimator based on the occurrence of zero returns. More recently, Abdi and Ranaldo (2017) develop a new estimator using closing high and low prices over two consecutive days. The Abdi and Ranaldo (2017) model, unlike the auto-covariance measure of Roll (1984), is independent of trade direction dynamics and uses daily high-low spreads, which are available over long time horizons. Other models are reported in Hasbrouck (2009), Corwin and Schultz (2012), Fong, Holden, and Trzcinka (2017), and Ibrahim and Kalaizoglou (2016).

#### *2.1.1.2 Zeros by Lesmond, Ogden, and Trzcinka (1999)*

Lesmond, Ogden, and Trzcinka (1999) introduce another liquidity proxy that captures the frequency of zero return days. In particular, it is defined as the ratio of number of days with zero return divided by the total number of observable days. The percentage of daily zero returns can be obtained for a period of a month or a year by computing the following formula:

$$Zeros_{it} = \frac{Zero\ daily\ returns_{it}}{D_{it}} \tag{2.2}$$

Where $Zeros_{it}$ is the frequency of days with return equal to zero for security i, over period of time t, $Zero\ daily\ returns_{it}$ is the number of zero return days of security i over the period of time t, and $D_{it}$ is the number of available trading days.

According to Lesmond, Ogden, and Trzcinka (1999), the frequency of zero daily return could be a measure of liquidity with some explanations. First, a higher illiquid stock faces more difficulty to trade, increasing the probability of these stocks having days with zero volume and return. Second, when the trading cost is high, and it is not compensated fully by gains from trading, investors with private information are less likely to trade. Hence, it leads to days with zero returns. Security with low transaction costs will have more frequent price movement and less zero returns, compared to a security with high transaction costs. Essentially, a zero return observation is a consequence of high transaction costs, thus the proportion of days with zero return in a period is used as a simple proxy for transaction costs. The higher the value of *Zeros*, the higher total transaction costs are.

The benefit of *Zeros* is that it provides estimates of transaction cost regardless of time period, stock exchange, or firms by only using time series daily return data. It allows transaction costs to be obtained more easily and inexpensively. In addition, this measure is arguably stronger than the effective spread of Roll (1984), as the model of Roll cannot provide estimates for more than half of the firms listed on the NYSE/AMEX exchange (Harris, 1990).

Furthermore, Lesmond, Ogden, and Trzcinka (1999) report a positive relationship between zero daily return and spread measures, including quoted bid-ask spread and Roll (1984) measure. Being consistent with this finding, using a sample of 19 emerging markets, Bekaert, Harvey, and Lundblad (2007) provide evidence that zero daily return is positively associated with bid-ask spread across all countries and negatively with turnover ratio. The wide employment of this measure in the academic literature also confirms the usefulness of it for the US market (Goyenko, Holden, and Trzcinka, 2009, and Fong, Holden, and Trzcinka, 2017) as well as for global financial markets (Lesmond, 2005; Chai, Faff, and Gharghori, 2010; and Lee, 2011).

Nevertheless, being similar to other liquidity proxies, *Zeros* also comes with limitations. In particular, Bekaert, Harvey, and Lundblad (2007) claim that days with zero returns may suggest other information associated with the equity market instead of stock liquidity. For instance, the days with zero returns are automatically observed with a lower level for a market with larger stocks. Furthermore, no trading days can occur due to a lack of information flow.

#### *2.1.1.3 High-Low spread of Corwin and Schultz (2012)*

Corwin and Schultz (2012) propose a new estimator of bid-ask spread called High-Low spread, which uses daily high and low prices only. They argue that “the sum of the price ranges over 2 consecutive single days reflect 2 days' volatility and twice the spread, while the price range over one 2-day period reflects 2 days' volatility and one spread". It allows them to derive an estimate of bid-ask spread as a function of the high to low price ratio. In particular, the High-Low spread is given by:

$$S_t = \frac{2(e^{\alpha t} - 1)}{1 + e^{\alpha t}} \tag{2.3}$$

$$\alpha_t = \frac{\sqrt{2\beta_t} - \sqrt{\beta_t}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma_t}{3 - 2\sqrt{2}}} \tag{2.4}$$

$$\beta_t = (h_{t+1} - l_{t+1})^2 + (h_t - l_t)^2 \tag{2.5}$$

$$\gamma_t = (\max\{h_{t+1}, h_t\} - \min\{l_{t+1}, l_t\})^2 \tag{2.6}$$

where $S_t$ is the High-Low spread of stock in day t, $h_t$ and $l_t$ are the observed high and low stock prices in day t, respectively. For a sample of D days, the High-Low spread is obtained by averaging the above two-day estimator. The negative two-day estimates are set to zero.

Corwin and Schultz (2012) argue that the stock's volatility and its bid-ask spread can be reflected by the daily price range as the high (low) prices are almost always buyer (seller) initiated. Hence, the High-Low spread is proposed as an estimator of stock liquidity. The major merit of the High-Low spread is that it has a relatively low standard deviation in low frequency data, which makes it a reliable proxy when only low frequency data are available (Bleaney and Li, 2015). Moreover, this spread is also easy to compute and it is not computer-time intensive. Thus, this liquidity measure is suitable for large samples over long time periods.

Using a US sample from 1993 and 2006, Corwin and Schultz (2012) report that their High-Low spread strongly correlates with the TAQ effective spread (correlation of 0.892). They also suggest that it outperforms other low-frequency spread measures, such as the Roll (1984) and the effective stick estimator of Holden (2009).

The major shortcoming of High-Low spread is that this method needs an adjustment for non-trading periods, such as holidays and weekends. This is because Corwin and Schultz

(2012) assume that the stock trades continuously while the market opens. Another assumption is that stock values do not change while the market is closed. In practice, these assumptions are violated, decreasing the accuracy of the High-Low spread.

#### 2.1.1.4 *Closing Percent Quoted Spread of Chung and Zhang (2014)*

An alternative low frequency estimator of the bid-ask spread is the Closing Percent Quoted Spread, introduced by Chung and Zhang (2014). This measure is constructed using daily closing bid and ask prices only and is regarded as a good proxy of effective spread. Closing Percent Quoted Spread is calculated as below:

$$Closing\ Percent\ Quoted\ Spread_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{Closing\ ask_{idt} - Closing\ bid_{idt}}{(Closing\ ask_{idt} + Closing\ bid_{idt})/2} \quad (2.7)$$

where $Closing\ Percent\ Quoted\ Spread_{it}$ is the Closing Percent Quoted Spread of stock i in the period of time t, $D_{it}$ is the number of trading days in time t, $Closing\ ask_{idt}$ and $Closing\ bid_{idt}$ are closing ask and bid prices of stock i in day d, respectively.

Closing Percent Quoted Spread is straightforward to compute and suitable for long time horizons, as it only requires daily closing ask and bid prices. Compared to prior liquidity proxies, it is relatively easier to calculate for both researchers and practitioners as this measure does not require a sophisticated estimation procedure or large computational efforts.

Using a US sample, Chung and Zhang (2014) compare the performance of their spread with previous low frequency spread estimators such as the Roll (1984) implicit effective spread and the *Zeros* measure of Lesmond, Ogden, and Trzcinka (1999). They imply that Closing Percent Quoted Spread provides a more thorough approximation of TAQ spread, compared to other liquidity measures in a cross-sectional setting. Furthermore, their spread measure is also highly correlated with the TAQ-based spread using both time-series and cross-sectional data, especially for NASDAQ stocks. When comparing different liquidity measures on 42 stock exchanges around the world, Fong, Holden, and Trzcinka (2017) suggest that Closing percent quoted spread is the best percent-cost proxy.

#### *2.1.1.5 AR spread of Abdi and Ranaldo (2017)*

Recently, Abdi and Ranaldo (2017) propose a new proxy (hereafter, AR) to measure stock liquidity, capturing the transaction cost dimension. Formally, it can be defined as follows:

$$AR_{it} = 2\sqrt{E[(c_{it} - \eta_{it})(c_{it} - \eta_{it+1})]} \tag{2.8}$$

where $AR_{it}$ is the Abdi and Ranaldo (2017) spread estimator of stock i in day t, $c_{it}$ is the close log-price of stock i, $\eta$ is the mid-point of the daily high and low log-price of stock i. Formally, it is given by:

$$\eta_{it} = \frac{h_{it} + l_{it}}{2} \tag{2.9}$$

The AR spread over a period of time is calculated as the average of daily measures. AR spread also has the benefit of data availability as it only uses close, high, and low prices. Despite being built based on the estimators of Roll (1984) and Corwin and Schultz (2012), the liquidity measure of Abdi and Ranaldo (2017) has some other advantages. First, it is independent of trade direction dynamics, and thus, it does not rely on bid-ask bounces to capture the effective spread like Roll (1984). Moreover, unlike Corwin and Schultz (2012), AR spread does require adjustment for non-trading periods.

According to Abdi and Ranaldo (2017), the AR spread has the highest correlations with TAQ effective spread, compared to other low frequency estimates. Furthermore, their measure also improves the systematic liquidity risk and commonality measurement of liquidity.

In summary, the five low-frequency proxies discussed in this section are good estimators of bid-ask spread. These estimators are also used to measure stock liquidity as they are useful in capturing market makers' reactions to news. However, they are not good at encapsulating long run financial stability. Hence, other liquidity measures such as price impact ratios are used in order to approximate financial stability.

### *2.1.2 Volume-based measures*

Volume-based liquidity measures distinguish between liquid and illiquid securities by the number of transactions. There is a close link between bid-ask spread and volume. A transaction can execute when the bid and ask price meet, thus a large bid-ask spread implies a low volume of security whereas a small bid-ask spread leads to a high trading volume of that stock. Meanwhile, there is also a causal effect of trading volume on the spread. Small trading volume adds more liquidity to stocks, and hence improves price accuracy and reduces spread (Sarkissian, 2016). Easley and O'Hara (1992) also suggest that volume has a positive impact on the size of spread. All else being equal, the greater volume leads to the larger spread due to the information component of the bid-ask spread.

According to Sarr and Lybek (2002), volume-based measures capture breadth and depth characteristics of a market or an asset. They are useful in measuring market breadth, which means that orders are both numerous and large in volume. Moreover, the number of transactions also provides valuable information for market dealers. Indeed, when there are large number of orders from both the selling and buying sides of the market, dealers are able to execute orders without taking risky inventory positions. As a result, volume-based measures are frequently used to measure liquidity. The common measures in this category are trading volume and turnover ratio.

#### *2.1.2.1 Trading Volume*

Trading volume is a straightforward proxy of liquidity. It is calculated as an amount of traded shares between market makers in buying and selling activities for a security i in a period t. Trading volume is usually calculated as dollar trading volume with the following formula:

$$DVol_{it} = \sum_{j=1}^{n} P_{ikt} \ x \ Vol_{ikt} \tag{2.10}$$

Where $DVol_{it}$ is the trading volume of a security i over time period t. It is calculated as the sum of the dollar value of $n$ transactions of stock i at period t. $P_{ikt}$ and $Vol_{ikt}$ are price and quantity of stock i for transaction k at time period t, respectively.

Alternatively, trading volume can be measured as the logarithm of the annual number of shares traded times the logarithm of closing price at the end of a calendar year as in Gregoriou and Nguyen (2010). When investigating the correlation between trading volume and average returns, Brennan, Chordia, and Subrahmanyam (1998) observe that they are negatively correlated, which is consistent with the notion that there is an influence of liquidity measures on stock returns (Amihud and Mendelson, 1986b). Supporting this finding, Chordia, Subrahmanyam, and Anshuman (2001) also provide evidence for the negative correlation between security returns and both the level and the variability of trading activities after book to market, size, and momentum effects have been controlled. Moreover, trading volume does matter in the adjustment of security price to information (Easley and O'Hara, 1992) and is a major determinant of the liquidity part of pricing (O'Hara, 2003).

Trading volume captures the trading activity of liquidity components, and by implication, it is considered as a proxy for liquidity. Stoll (1978) suggests that dollar trading volume has a positive relationship to the holding cost of dealers. Hence, it is an influential determinant of liquidity. The higher trading volume, the lower security illiquidity. Furthermore, Chordia, Roll, and Subrahmanyam (2000) also show a strong correlation between trading volume and quoted depth, and other proxies of liquidity. Although being popular in the application (Lee, 1993; Chordia, Subrahmanyam, and Anshuman, 2001; and Becker-Blease and Paul, 2006), trading volume is considered as an inappropriate liquidity measure due to the double counting issue.

#### *2.1.2.2 Turnover ratio*

Another volume based measure of liquidity is the turnover ratio. It can be calculated as the number of traded shares divided by the number of shares outstanding.

$$Turnover_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{Vol_{idt}}{Shr\Box ut_{idt}} \tag{2.11}$$

where $Turnover_{it}$ is the turnover ratio of stock i over time period t. $D_{it}$ is the number of trading days. $Vol_{idt}$ and $Shrout_{idt}$ are the daily number of shares traded and daily number of shares outstanding of stock i, respectively.

According to Easley and O'Hara (1992) and Engle and Russell (1998), trading frequency carries information of the market and bears a significant weighting on liquidity. Turnover captures trading frequency, thus when liquidity is not examined directly, one can use this rate as a method to measure stock liquidity. Moreover, turnover ratio is considered to be a more suitable liquidity measure compared to trading volume as it accounts for market capitalization of stocks (Gabrielsen, Marzo, and Zagaglia, 2011). Turnover ratio is easy to obtain because of the availability of data on a monthly and daily basis. This allows the capturing of liquidity for numerous stocks over a long time period. Due to these advantages of turnover ratio, it is employed as a proxy of liquidity in other research such as Rouwenhorst (1999), Chordia, Subrahmanyam, and Anshuman (2001), Nguyen et al. (2007), and Brown, Crocker, and Foerster (2009). Using both time-series and cross-sectional regressions tests, Nguyen et al. (2007) show evidence for the significance and negative correlation between turnover and asset returns, whereas Rouwenhorst (1999) and Brown, Crocker, and Foerster (2009) provide inconsistent results.

On the other hand, Lee and Swaminathan (2000) argue that turnover ratio may provide information other than liquidity. They find a low degree of correlation between this ratio and firm size, and relative spread. Further, they provide evidence that turnover relates to stock's past performance as firms with low past turnover rates earn a higher future return. Lesmond (2005) argues that there is a scaling problem with turnover as this measure is likely to be nonlinear with respect to the bid-ask spread. Hence, turnover may be a less than perfect liquidity approximation.

With the above advantages and disadvantages of volume based measures (i.e. trading volume and turnover ratio) as a proxy for liquidity, there is still an issue that arises from using both measures. According to Gabrielsen, Marzo, and Zagaglia (2011) volume based liquidity measures fail to show how price changes by the arrival of sudden orders. These proxies are not built based on theoretical models of market maker behaviour, thus they only capture the past performance of prices and volume changes. Hence, they suggest that these measures are only a useful starting point in the analysis process.

### *2.1.3 Price impact-based measures*

#### *2.1.3.1 Amihud (2002) Illiquidity ratio*

The illiquidity measure introduced by Amihud (2002) is the most commonly used price impact ratio in the finance literature. In particular, the illiquidity ratio reflects the sensitivity of average absolute daily price to $1 trading volume for a stock, it is also referred to as the return to volume ratio. The average of daily impacts over a sample period is calculated as follows:

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{Dvol_{idt}} \tag{2.12}$$

Where $RtoV_{it}$ is the illiquidity ratio of stock i in the period t, $D_{it}$ is the number of trading days in the period t for stock i, $R_{idt}$ is the return of stock i on day d in the period t, and $Dvol_{idt}$ is the dollar volume of stock i on day d in the period t. The stock is said to be illiquid if the return to volume RtoV ratio is high. It implies that stock price moves in a great capacity when there is little volume change.

The Amihud (2002) illiquidity ratio exhibits some advantages over other liquidity measures. First, this ratio is computed using readily available data on daily return and volume. It allows researchers to compute the illiquidity ratio for days over long time periods for most financial markets. The detailed transaction data in some markets, especially emerging markets, are not widely available, which limits the usage of trading cost based liquidity measures in academic research. Therefore, the illiquidity ratio provides a proxy from available data for these markets to deal with this issue. Second, the return to volume ratio captures the effects of trading volume on the movements of security prices and transforms it into transaction costs (Acharya and Pedersen, 2005). It can be seen from the ratio's formula that higher trading volume leads to a lower illiquidity ratio. Meanwhile, Lou and Shu (2017) suggest that the value of the Amihud return to volume ratio is its correlation with trading volume, which enables this ratio to measure price impact comprehensively via its trading volume component.

In spite of the fact that return to volume ratio is a useful and convenient measure for illiquidity, there are still some limitations. First, it is associated with a significant size bias. Cochrane (2005) argues that for two stocks with the same turnover, the stock with larger market capitalization is automatically less illiquidity only because of its size. As a consequence, the illiquidity ratio is incomparable across stocks with different market values (Florackis, Gregoriou, and Kostakis, 2011). Second, Florackis et al. (2011) also argue that it fails to reflect the trading frequency aspect of liquidity. They suggest that trading frequency is becoming a dominant issue, and it affects the required premium. However, Amihud's ratio assumes that trading frequency is similar across stocks, and thus it should not influence on liquidity premia. This assumption is unrealistic due to the considerable cross-sectional and time-series variation of trading frequency (Datar, Naik, and Radcliffe, 1998).

#### *2.1.3.2 Florackis, Gregoriou, and Kostakis (2011) price impact ratio*

Florackis, Gregoriou, and Kostakis (2011) introduce a new price impact ratio to capture liquidity. In particular, it is proposed as an alternative to the Amihud (2002) illiquidity ratio.

According to Florackis, Gregoriou, and Kostakis (2011), there are two main limitations of the Amihud (2002) return to volume ratio, namely cross-sectional size bias and the assumption of similar trading frequency across stocks. It is noticeable that the trading volume, which appears in the denominator of the Amihud (2002) ratio, is very highly correlated with the market value of stocks. Furthermore, they also argue that return to volume ratio fails to account for the trading frequency of securities. Datar, Naik, and Radcliffe (1998) find that trading frequency has a strong effect on asset pricing.

Florackis, Gregoriou, and Kostakis (2011) develop a new liquidity measure defined as the absolute return scaled by the turnover ratio (henceforth RtoTR). Formally, it is defined as the following:

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TR_{idt}} \tag{2.13}$$

where $RtoTR_{it}$ is the return to turnover ratio of stock i in a period of time t, $D_{it}$ is the number of valid trading days of security i over time t, $R_{idt}$ is the daily return of security i in day d, and $TR_{idt}$ is the turnover ratio of security i in day d.

It can be seen from the formulas of the RtoV and RtoTR ratios that trading volume in the denominator of the former is substituted by turnover ratio in the latter. As a result, the RtoTR ratio has a similar intuitive interpretation that reflects the change in stock price to one percent of turnover ratio.

As highlighted by Florackis, Gregoriou, and Kostakis (2011), this new measure not only takes into account the benefits of the Amihud (2002) illiquidity ratio but it also has some other appealing features. In particular, their liquidity proxy inherits the easy access and data availability of the Amihud ratio. Furthermore, the RtoTR ratio overcomes one of the big drawbacks of the Amihud (2002) return to volume ratio, namely the size bias, as there is no empirical association between firm size and turnover ratio.

They argue that the return to turnover ratio is more comprehensive because it combines trading costs and frequency effects. According to proposition 1 of Amihud, Mendelson, and

Pedersen (2005), the expected return on security i for a risk-neutral investor is given by the following equation:

$$E(r^i) = r^f + \mu \frac{C^i}{P^i} \tag{2.14}$$

where $C^i$ and $P^i$ represent the transaction costs and price of asset i, respectively, and μ is the trading intensity of the investor. It can be seen that both transaction cost and trading frequency positively correlate with the expected return. Therefore, asset prices are affected by a compound effect of both aspects, not each aspect in isolation.

*2.1.3.3 Free float adjusted price impact ratio.*

An alternative price impact ratio is developed by Karim et al. (2016). It is a modification of the Florackis, Gregoriou, and Kostakis (2011) RtoTR ratio, with the consideration of the free float factor. The new liquidity measure is given by:

$$RtoTRF_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TRF_{idt}} \tag{2.15}$$

Where $RtoTRF_{it}$ is return to turnover ratio adjusted with the public free float factor of stock i over time period t, $D_{it}$ is the number of available trading days for security i for the period of time t, $R_{idt}$ is daily return of stock i, and $RTF_{idt}$ is the corresponding turnover ratio captured by the free float percentage. $RTF_{idt}$ is calculated as trading volume divided by the multiplication of the number of share outstanding and the public free float factor.

Formally, compared to the RtoTR ratio of Florackis, Gregoriou, and Kostakis (2011) the new liquidity proxy replaces the turnover ratio in the denominator component by adjusted turnover ratio controlling for the public free float factor. The adjusted turnover ratio increases the encapsulation power of price impact, which is defined as the ability of the ratio to approximately capture the cross-sectional variability of the turnover ratio of the security. Lam, Lin, and Michayluk (2011) argue that the free float factor and liquidity are correlated together as the higher supply of the stock makes it easier to trade. Hence, they suggest that measures should consider the supply ability of the stock to truly capture the liquidity.

Karim et al. (2016) argue that the RtoTRF ratio inherits some benefits of the RtoTR ratio of Florackis et al. (2011). First, data for calculating the new ratio is simple and available to obtain. Second, it is free of size bias as being explained earlier. Furthermore, the denominator of the RtoTRF ratio includes turnover ratio, which controls the impact of trading frequency on asset pricing. The new liquidity proxy-RtoTRF not only inherits the benefits of the RtoTR ratio, but it also has additional appealing features. In particular, the RtoTRF ratio appeals in terms of the "real supply" of available shares to the public by taking into account the public free float factor. The number of shares outstanding is not the stock supply to the public, which implies that the turnover alone does not indicate the real number of shares traded. Therefore, the proposed measure is expected to be more suitable in estimating the price impact aspect of stock liquidity.

In order to test the advantages of the RtoTRF ratio, my third chapter examines the relationship between liquidity and asset prices using three different price impact ratios, including the RtoV, RtoTR, and RtoTRF ratios for comparison purposes. Using a sample of all U.S public companies over the period from 1997 to 2017, I show that the free float adjusted price impact ratio is superior to the other two price impact ratios. In particular, this chapter argues that more liquid stocks (low RtoTR or RtoTRF ratios) yield higher returns than less liquid stocks. It can be explained by a trading frequency argument, liquid stocks may get traded more frequently, and thus they have greater returns. This finding is also robust to the global financial crisis over the time period 2007-2009.

#### *2.1.4 Multi-dimension based measure*

##### *2.1.4.1 Turnover –adjusted number of zero daily trading volume (Liu, 2006)*

Liu (2006) introduces a turnover–adjusted number of days with zero trading volume liquidity measure. Liu (2006)'s liquidity proxy of a security is calculated using the equation below:

$$LM_{it} = \left[ NoZV_{it} + \frac{1/(turnover_{it})}{Deflator} \right] x \ \frac{21}{NoTD_t} \tag{2.16}$$

where $LM_{it}$ is the turnover-adjusted number of zero daily trading volume of stock i in month t, $NoZV_{it}$ is the number of days with zero volume of stock i in month t, $Turnover_{it}$ is the sum of daily turnover of stock i in month t, $NoTD_t$ is the total number of trading days in the market in month t, and *Deflator* is 480000 as suggested by Liu (2006). Deflator is chosen to make sure that $0 < \frac{1/(xmonth\ turnover)}{Deflator} < 1$. Thus, stocks with similar days of zero volume may be further distinguished.

Liu (2006)'s measure considers multiple dimensions of liquidity, including trading quantity, trading speed, and trading cost with a particular focus on trading speed. More specifically, the figure of days with zero volume reflects the continuity of trading as well as the potential delay or challenge in executing an order. A stock with a higher number of zero daily volume is less likely to be traded and thus less liquid. The role of daily zero volume in this measure is similar to the number of days with zero returns in Lesmond, Ogden, Trzcinka (1999), and thus this measure captures the trading cost dimension. Furthermore, for stocks with the same number of days with zero volume, the turnover ratio is used to distinguish the liquidity level between them.

As noted by Liu (2006), this new measure is highly related to other liquidity proxies such as turnover ratio and return to volume ratio. Other studies employ the Liu (2006) measure in investigating stock liquidity, such as Chai, Faff, and Gharghori (2010) and Lam and Tam (2011).

### 2.1.5 Issues in low frequency liquidity measurement

One of the main benefits of using low-frequency data to calculate liquidity is that it saves significant computation time compared to using high frequency data (intraday data) (Holden, Jacobsen, and Subrahmanyam, 2014). The daily data is also available over long time horizons for most stock exchanges. Hence, low frequency liquidity measures are applied in many academic studies. Specifically, asset pricing literature has shown that liquidity is a priced risk factor not only in the US market (see, Chordia, Roll, and Subrahmanyam, 2000; Acharya and Pedersen, 2005; and Hasbrouck, 2009), but also for emerging markets (Bekaert, Harvey, and Lundblad, 2007). Hence, a high-performing low frequency proxy of liquidity will provide a precious contribution to the asset pricing literature. It motivates researchers to propose and introduce new low frequency liquidity proxies of high frequency measures. For instance, due to the lack of long term intraday data and computational difficulties in calculating bid-ask spread, Roll (1984) implicit effective spread and *Zeros* of Lesmond, Ogden, and Trzcinka (1999) mentioned above are the first measures to estimate transaction costs using price data and daily data. Hasbrouck (2009) develops an alternative proxy for the effective spread with a Gibbs procedure, whereas Holden (2009) also introduces an extended Roll (1984) model. Chung and Zhang (2014) suggest a percent-cost proxy called "Closing percent quoted spread" using closing ask and bid prices only, and most recently the AR spread is introduced by Abdi and Ranaldo (2017).

Thus far, a wide range of researchers has applied these low frequency estimators in their analysis. However, the question is how well these measures capture standard benchmarks, which are calculated from intraday data, and whether they really measure liquidity. In order to answer this question, several studies have evaluated the performance of these low frequency liquidity measures in stock markets. For example, Goyenko, Holden, and Trzcinka (2009) compare a large number of widely used liquidity proxies to liquidity benchmarks from high frequency data. Using a US data sample, they discover that both monthly and annual low frequency proxies are good at capturing high-frequency measures of transaction costs. Chung and Zhang (2014) report that the Closing percent quoted spread performs better than the Roll (1984) and *Zeros* estimator in the US market. The most comprehensive study is conducted by Fong, Holden, and Trzcinka (2017), who investigate liquidity proxies worldwide. They extend the study of Goyenko, Holden, and Trzcinka (2009) by comparing a wide range of monthly liquidity measures calculated from daily data to the high frequency liquidity measures. These are computed from the new global intraday equity database entitled Thomson Reuters Tick History (TRTH). Their sample includes intraday data for 42 markets around the world. They find that the daily version of the Amihud price impact ratio is the best daily proxy for cost-per-volume, whereas Closing percent quoted spread is the best daily percent-cost proxy.

Nevertheless, Jahan-Parvar and Zikes (2019) have established that low frequency liquidity measures do not really capture transaction costs. They compare some popular daily data-based measures of transaction costs with their high frequency data-based measures. They argue that low frequency measures are highly upwardly bias and imprecise for US equities and foreign exchange rates. They also suggest that caution is need when applying these measures to asset pricing. Even though numerous proxies have been developed to measure low frequency stock liquidity, their accuracy and ability to capture transaction costs, can be improved further. Avenues of future research should be along the lines of developing low frequency liquidity measures that are free of bias.

Another limitation of low frequency liquidity measures is that they fail to capture market microstructure noise. Noise in transaction data is prevalent at high frequency (Ait-Sahalia and Yu, 2008). Market microstructure noise includes a range of frictions that arise due to the imperfection of the trading process such as bid-ask bounces, price changes' discreteness, inventory holdings, price impacts of large orders and other source of friction. These noises bias the results of empirical asset pricing. Moreover, according to Zhang, Mykland, and Ait-Sahalia

(2005), market microstructure noise has different behaviour over alternative frequencies with very high frequency data mostly composed of market microstructure noise. Awartani, Corradi, and Distaso (2009) study the changes in microstructure noise due to sampling frequency and suggest that noise has a statistically significant effect on volatility estimators at frequencies of 2-3 minutes or higher. Therefore, the high frequency liquidity measures are better in reflecting market frictions.

## 2.2 Stock Return and Asset Pricing Model

What is the relationship between risk and expected stock return? It is a primary question of finance which researchers are still seeking for the answer. The first discussion of the theory of stock price behaviour is of Markowitz (1959). Markowitz proposes a single-period portfolio choice model in which investors form a portfolio at the beginning of the period. This model assumes that investors are risk averse and are only concerned with the mean and variance of their investment return as the basic criteria for portfolio optimization. Based on this framework, the capital asset pricing model (CAPM) is the first standard asset pricing model proposed and widely used in research and practice.  As a result of CAPM developments, several models have been introduced by applying additional financial variables in the models, such as the Fama and French three-factor model, Carhart four-factor model and the Fama and French five-factor model. This section reviews various asset pricing models which are widely used by researchers and investors. They are also applied in this thesis when considering asset prices.

### 2.2.1 The Capital Asset Pricing Model (CAPM)

The CAPM is built on the premise of the mean-variance framework of Markowitz (1959) by Sharpe (1964) and Lintner (1965). This model provides an insight into the kind of risk correlated to stock return with the idea that asset prices may not reflect all related risk. Specifically, the Sharpe-Linter model indicates that the expected excess return of a security is a linear function of systematic or market risk with the following equation:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \varepsilon_{it} \tag{2.17}$$

where

$R_{it}$ : is the return of portfolio i for period t

$R_{ft}$ : is risk-free rate return for period t

$\alpha_i$: is the intercept term for portfolio i

$\beta_{i,MKT}$: is the exposure of portfolio i to the market return

$MKT_t$: is the market excess return calculated by subtracting the risk free rate from market portfolio return for period t.

$\varepsilon_{it}$: is the error term for portfolio i for period t

Beta ($\beta$) is the most important factor in this model as it measures the systematic risk of a stock or the sensitivity of the expected excess stock return. Due to providing a simple and powerful tool to estimating risk and the association between risk and expected stock return, the CAPM have become an attractive asset pricing model in applications. The article of Black, Jensen, and Scholes (1972) is one of the first papers that provides some empirical tests on the CAPM. Using the sample of stocks listed on the New York Stock Exchange (NYSE) from 1931 to 1965, they provide the supporting evidence for the above model by showing that the Beta factor is an important determinant of stock return. This model is applied to a wide range of stock markets, from developed to developing stock markets.

However, numerous empirical studies have shown that the CAPM fails in fully explaining the expected stock return. Indeed, the CAPM is a single period model based on some unrealistic assumptions, including complete agreement and either unrestricted risk-free borrowing and lending or unrestricted short selling of risky assets (Fama and French, 2004). For instance, Banz (1981) provides evidence that size measured by market equity also contributes to the explanations of cross-sectional stock returns. Later, Bhandari (1988) also suggests a positive correlation between leverage and stock returns. Other factors are shown to be related to stock returns, such as book to market ratio (Stattman, 1980; Rosenberg, Reid, and Lanstein, 1985) and the earnings price ratio (Basu, 1983). Fama and French (1992) provide a summary of previous empirical studies on CAPM and examine the univariate relationship between average stock return, size, leverage, book-to-market ratio, and earnings price ratio. They conclude that the relation between Beta and average return for 1941-1990 is weak and the CAPM does not describe the average stock return of the US stock exchange in this period. These findings diminish the credence on the CAPM's efficiency and motivate the development and modifications of asset pricing models.

### 2.2.2 Fama and French three-factor model

Fama and French (1993) introduce an alternative asset pricing model by adding two risk factors to the CAPM, including size and value factors to achieve superior explanatory power on stock return with the equation as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{it} \qquad (2.18)$$

where

$SMB_t$: stands for the size factor, calculated as the difference between the return on small stock portfolios and return on large stock portfolios.

$HML_t$: stands for the value risk factor, defined as the difference between the return on the portfolio of high-book-to-market stocks and the return on the portfolio of low-book-to-market stocks.

$\beta_{i,MKT}$, $\beta_{i,SMB}$, $\beta_{i,HML}$ are the exposures of portfolio i to market return, SMB, and HML, respectively. Other variables are defined as in equation (2.17).

As the Fama and French three-factor model (3FF) is constructed based on the results of empirical research, rather than economic axiom, thus it is difficult to interpret the findings in a theoretical context. Fama and French (1998) extend the model to a global context using the data from 13 markets and show that the two factor model, including the global market return and global book-to-market equity outperforms the CAPM in explaining the value premium. Numerous studies have shown supporting evidence on the efficiency of the Fama and French three-factor model in explaining the variation of stock return (among others, Chan, Hamao, and Lakonishok, 1991; Fama and French, 1996; 1998; Liew and Vassalou, 2000; Al-Horani, Pope and Stark, 2003; Drew, Tony, and Veeraragavan, 2005). Griffin (2002) compares the world three-factor model and country-specific model. Using regressions for both portfolio and individual stock, he reports that the domestic model explains more of the variation in return, compared to the world factor model. Fama and French (2012) provide evidence that the three-factor model is better than CAPM in explaining average stock return using international stock exchanges. Nevertheless, Kothari, Shanken, and Sloan (1995) re-examine the results of Fama and French (1993) and indicate that there are a combination of survivorship bias driving the results. Daniel and Titman (2012) find other characteristic that explains the cross-sectional variation in stock return, rather than pervasive factors.

### 2.2.3 Carhart four-factor model

Although the Fama and French three-factor model have been shown to be better than the CAPM in capturing variance in stock return, Jegadeesh and Timan (1993) argue that it cannot fully explain these variations and provide evidence that the performance of stocks in the past affects their expected stock returns. To capture this effect, Carhart (1997) proposes a new asset pricing model by adding a momentum factor to the three factor model.

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,MOM} MOM_t + \varepsilon_{it} \qquad (2.19)$$

where

$MOM_t$: stands for the past performance factor (momentum factor). It is calculated as the difference between winners and losers. Other variables are defined as in equation (2.18).

The Carhart four -factor model is then used in several studies in different stock markets (see, e.g., Bauman et al., 1998; Brav et al., 2000; Jegadeesh, 2000; Liew and Vassalou, 2000). However, the performance of the Carhart four-factor model is criticized. Hou, Xue, and Zhang (2014) provide evidence that their q-factor model performs better than the three-factor and four-factor model in capturing return anomalies.

### 2.2.4 Fama and French five factor model

Given that Fama and French three-factor model does not explain anomalies or cross-sectional variation in expected returns particularly related to profitability and investment, Fama and French (2015) construct a new asset pricing model by adding profitability and investment factors to the three factor model. This model has the following equation:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \beta_{i,RMW} RMW_t + \beta_{i,CMA} CMA_t + \varepsilon_{it} \quad (2.20)$$

where

$RMW_t$ : is the profitability factor, defined as the return spread of the most profitable portfolio minus the least profitable portfolio.

$CMA_t$: stands for investment factor, calculated as the return spread of the conservative investment portfolio minus aggressive investment portfolio. Other variables are defined as in equation (2.18).

Numerous studies investigate the performance of the five-factor model in different stock markets, such as the UK (Nichol and Dowling, 2014), Australia (Chiah et al., 2016), and Japan (Kubota and Takehara, 2018). In a later study, Fama and French (2017) extend the five-factor model to an international context which covers North America, Europe, and the Asia Pacific. They show that the five-factor model largely absorbs the patterns in average return.

Nevertheless, empirical studies on asset pricing models have shown that more factors are not always better. Fama and French (2015, 2018) show that the five-factor model fails to capture fully the low average returns of small stocks whose returns behave like those of low profitability firms that invest aggressively. Ekaputra and Sutrisno (2020) examine the performance of the Fama and French three-factor model and five-factor model in Singapore and Indonesia and find that the five factor model is not better than the three factor model in taking account of excess returns.

## 2.3 Conclusion

This chapter reviews the literature on liquidity measures and asset pricing. Although some proxies are proposed to measure stock liquidity, the jury is still out on the best approximation of liquidity. Many studies in both developed markets such as the US, UK and emerging markets are conducted to test the accuracy of different liquidity measures. In this chapter, I focus on literature review of low frequency liquidity measures which are based on low frequency data (daily data). Due to the availability of low frequency data, especially for developing markets, these measures are widely used in the academic literature when examining liquidity of stocks.

Chapter 2 reviews liquidity measures in four groups that capture one or more liquidity dimensions, including trading cost, price impact, trading volume, and multi-dimension measures. For each liquidity proxy, this chapter discusses the advantages and disadvantages. The chapter suggests that liquidity measures, which capture the trading cost dimension are good estimators of bid-ask spread, but they are not good at encapsulating long run financial stability, compared to price impact ratios. Moreover, recent measures are proposed to overcome the disadvantages of prior proxies. For example, compared to other bid-ask spread proxies, the Closing Percent Quoted Spread of Chung and Zhang (2014) provides a more thorough approximation of TAQ spread, and is highly correlated with the TAQ-based spread using both time-series and cross-sectional data. I also review how liquidity relates to asset pricing using evidence from various liquidity proxies in different stock markets. The asset pricing literature has shown that liquidity is a priced risk factor not only in the US market, but also for emerging markets. Finally, this chapter discusses the main issue when using daily data to compute stock liquidity. Jahan-Parvar and Zikes (2019) have argued that low frequency liquidity measures do not really capture transaction costs as they are highly upwardly bias and imprecise for US equities and foreign exchange rates. In addition, low frequency liquidity measures fail to capture market microstructure noise, thus leading to a bias in the results of empirical asset pricing. Even though the liquidity approximations discussed in this review are widely used, the literature is not convinced by their ability to capture standard liquidity benchmarks calculated from intraday data. It is still an open question and will continue to be an avenue for future research in liquidity.

Although there are different liquidity measures which capture one or more dimensions of stock liquidity, I mainly employ price impact ratios as liquidity proxies for the next empirical chapters due to the following reasons. First, they have a simple construction using daily data to capture price impact. For example, the return to turnover ratio of Florackis et al. (2011) is computed using readily available data on daily return, volume and shares outstanding. Previous studies also provide evidence concerning the strong relation between return to volume ratio of Amihud (2002) and high-frequency benchmarks (Hasbrouck, 2009; Goyenko, Holden, and Trzcinka, 2009). Moreover, liquidity measures which capture the price impact dimension are superior in reflecting the long-term volatility of stock. Hence, I focus on price impact ratios instead of traditional liquidity measures such as bid-ask spreads.

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# CHAPTER 3: LIQUIDITY AND ASSET PRICING: EVIDENCE FROM A NEW FREE FLOAT ADJUSTED PRICE IMPACT RATIO

## 3.1 Introduction

Liquidity, defined as the ability to trade stocks quickly, anonymously, and with little price impact, is one of the most fundamental components of financial research. The growing interest in liquidity and its impact on financial markets, has resulted in the establishment of several liquidity measures by academic scholars. These measures capture different dimensions of liquidity, including trading quantity, cost, speed, and price impact. One of the most widely used liquidity proxies is the Amihud illiquidity ratio, known in the literature as the return to volume ratio (Amihud, 2002). It reflects the change of security prices when a number of stocks are traded. The return to volume ratio (hereby RtoV ratio) is used in thousands of research manuscripts because of its straightforward computation, easy interpretation, and for its accurate approximation of liquidity[2]. Amihud (2002) treats volume as a measure of trading activity as it captures the transaction costs. When comparing several liquidity measures, Goyenko, Holden, and Trzcinka (2009) provide evidence that the Amihud illiquidity ratio measures price impact with a high level of accuracy. However, the return to volume ratio also comes with some limitations. First, the ratio exhibits a firm size bias as there is a solid positive relationship between trading volume and firm's market capitalization (MV). Indeed, small capitalization stocks (usually small trading volume) are expected to have a higher RtoV ratio than big capitalization stocks with higher trading volume. As a result, it leads to an automatic conclusion that small stocks are less liquid than larger securities. Another shortcoming of the return to volume ratio is that it fails to reflect the trading frequency aspect of stock liquidity. Amihud

[2] Approximately six thousand papers have cited Amihud (2002) paper (as reported by Google Scholar in October 2018).

and Mendelson (1986b) show in a theoretical framework that security liquidity is related to trading frequency.

An alternative price impact ratio is proposed by Florackis, Gregoriou, and Kostakis (2011), namely, the return to turnover ratio (hereby RtoTR ratio), which is defined as the ratio of daily absolute stock return to turnover. By replacing trading volume with the turnover ratio in the denominator of the Amihud ratio, the RtoTR ratio not only inherits the advantages of the RtoV ratio, but also overcomes its disadvantages. In particular, as the data for the turnover ratio is easy to obtain, the RtoTR ratio also has the advantage of simplicity and data availability. Turnover ratio is not positively correlated with market capitalization, which implies that the return to turnover ratio is free of size bias. Moreover, employing turnover in calculating liquidity measures allows the RtoTR ratio to control both the effect of trading costs and trading frequency on asset pricing. Using all listed UK companies from 1991 to 2008, Florackis, Gregoriou, and Kostakis (2011) provide evidence that the RtoTR ratio is free of size bias and that there is a combination effect of trading costs and trading frequency on asset pricing.

Nevertheless, there is an issue with both the RtoV and RtoTR ratios, which has not been mentioned in the Florackis, Gregoriou, and Kostakis (2011) study. The problem is that the number of shares outstanding used in constructing these liquidity proxies does not reflect the real number of available stocks that are available to the public for trading. Lam, Lin, and Michayluk (2011) argue that the number of available shares (public free float factor) and liquidity are correlated as the higher supply of the stock makes it easier to trade. Hence, they suggest that a liquidity measure should consider the supply ability of stocks in predicting trading costs. In this study I aim to test the efficiency of a new price impact ratio – the free float adjusted price impact ratio introduced by Karim et al. (2016). This new liquidity measure replaces the turnover ratio in the denominator component of the RtoTR ratio by adjusted turnover ratio controlling for the public free float factor. The adjusted turnover ratio increases the encapsulation power of price impact, which is defined as the ability of the ratio to approximately capture the cross-sectional variability turnover ratio of the security.

The free float adjusted price impact ratio (hereby RtoTRF ratio) not only inherits the benefits of the RtoTR ratio but also has additional appealing features. In particular, the RtoTRF ratio incorporates the “real supply” of available shares to the public by taking into account the public free float factor. Therefore, the proposed measure is expected to be a more accurate measure of stock liquidity than the RtoV and RtoTR ratios. The RtoTRF ratio eliminates the size bias and trading frequency issues of the Amihud ratio, and is based on the real supply of assets available for trading, which is not the case for the Florackis, Gregoriou, and Kostakis (2011) ratio[3].

This chapter provides new evidence on the impact of liquidity on asset pricing by employing price impact ratios to measure liquidity. In particular, I conduct analysis using three alternative price impact ratios as proxies for stock liquidity for comparison purposes. This chapter implements the Amihud ratio, the return to turnover ratio by Florackis, Gregoriou, and Kostakis (2011), and the free-float adjusted price impact ratio by Karim et al. (2016). I focus on price impact ratios instead of traditional liquidity measures such as bid-ask spreads due to the following reasons. First, liquidity measures that capture the price impact dimension are better in reflecting the long-term volatility of stock. This also explains the overwhelming usage of the Amihud ratio in the previous academic literature. Second, despite measuring the transaction costs, bid-ask spreads do not capture the actual costs of a trade. Roll (1984) finds that actual transactions are executed mostly within the quoted bid-ask spreads, not exactly at

[3] This chapter is different from Karim et al. (2016), who apply the free float adjusted price impact ratio to stock liquidity in the Malaysian stock market. I focus on the relationship between stock liquidity and security return in the US market. Given the size and importance of the US equity markets globally, I believe that my chapter provides a fundamental empirical contribution to the free float adjusted price impact ratio.

the quoted prices, which are assumed in the computation of bid-ask spreads. In addition, the daily bid-ask spreads may be noisy and uninformative as they are usually wider for large price stocks. The spreads may be good at reflecting the price changes around news but they do not capture the long-term financial stability of an asset. Hence, the bid-ask spread is not a good proxy for liquidity (Peterson and Fialkowski, 1994). One of the key factors in determining the accuracy of stock market efficiency tests is to use accurate measures of liquidity (Lesmond, 2005). Amihud and Mendelson (1986b) also argue that the liquidity proxies have an influence on determining the stock return. Therefore, the accuracy of liquidity measures plays an important role in asset pricing tests further motivating my research study.

In order to examine the relationship between stock liquidity and expected stock returns, I use a sample of listed stocks in the three main stock exchanges of the US market, including the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and National Association of Securities Dealers Automated Quotations (NASDAQ) over the time period of 1997-2017. Specifically, stocks are ranked each month on the basis of each liquidity measure and then constructed on 25 decile portfolios. For comparison purposes, I use three alternative price impact ratios as a proxy for liquidity, namely the RtoV, RtoTR, and RtoTRF ratios. This chapter finds a positive relationship between average stock return of decile portfolios and the level of RtoV ratio. Indeed, stocks with low RtoV value (high liquidity) have lower returns compared to stocks with high return to volume ratios. This evidence is consistent with previous studies such as Amihud (2002) and Nguyen et al. (2007). However, a puzzling result is that a decrease in the liquidity level leads to a decline in stock returns when using the RtoTR and RtoTRF ratios as liquidity measures. In particular, more liquid stocks (low RtoTR or RtoTRF ratios) yield higher returns than less liquid stocks. The spread between the average value-weighted returns of the top and bottom decile portfolios is 28.017% per year for portfolios sorted on the basis of RtoTRF ratio, and 20.229% per year for portfolios sorted by the RtoTR ratio. This is surprising because, according to the Capital Asset Pricing Model (CAPM), the higher risk is correlated with the higher expected return. However, it can be explained by a trading frequency argument, liquid stocks may get traded more frequently, and thus they have greater returns. This finding is consistent with the information-trading hypothesis of Wilcox (1993), which suggests that a delay in trading execution can lessen the security return of an active investor with predictive information. The sample is also divided into two sub periods to capture the influence of the global financial crises between 2007-2009 on asset pricing and liquidity. The pre-financial crisis period is defined as 1997-2007 and the post-financial crisis period is as 2008-2017[4]. Similar results are seen in both subsamples when considering portfolios sorted by the RtoTRF ratio. The findings of this chapter support the argument of Florackis, Gregoriou, and Kostakis (2011), which states that both trading costs and trading frequency are important factors in asset pricing and the former is dominated by the latter effect.

In addition, using the time-series tests I find that risk adjusted return of portfolios constructed on the basis of RtoTRF ratio is higher as compared to the returns of portfolios sorted based on RtoTR ratio. This suggests that the free float adjusted price impact ratio has superior performance than the RtoTR ratio in the US market. Further evidence of abnormal portfolios' returns is provided using the Fama and MacBeth (1973) cross-sectional regression. Following Florackis, Gregoriou, and Kostakis (2011), a price factor (PI) is added to the asset pricing models to examine whether the PI-adjusted models can explain the anomalies. There is a positive and significant correlation between PI and average portfolio return when using the RtoTR and RtoTRF ratios to assign stocks on decile portfolios. This implies that the price factor can partly explain the anomalies.

[4] Following Fong, Holden, and Trzcinka (2017), this chapter considers two sub-periods, including 1997-2007 and 2008-2017, in order to study the effect of the 2007-2009 financial crisis on liquidity.

This chapter contributes to the previous literature in the following ways. First, to the best of my knowledge, this is the first study to provide empirical US evidence on the influence of liquidity on asset prices using the free float adjusted price impact ratio (Karim et al., 2016) as a liquidity proxy. I use, in my opinion, the best approximation of liquidity in the market microstructure literature to date for the reasons mentioned previously. This will enable to capture the impact of liquidity on asset pricing in a more accurate manner than in previous research. Given the lack of empirical studies on liquidity and asset pricing and the importance of the topic pre and post the 2007-2009 financial crises, this chapter provides an important contribution to the literature.

Second, the price impact ratio proposed by Florackis, Gregoriou, and Kostakis (2011) – the return to turnover ratio (RtoTR) has proved that it is priced in stock returns using data from the London stock exchange over the period 1991-2008. In particular, they find that stocks with a low RtoTR ratio have higher post-ranking returns compared to high RtoTR ratio stocks. This chapter tests whether this result holds for the US equity market, which provides a robustness test for the quality of the RtoTR liquidity measure.

Moreover, this chapter contributes to the literature in understanding the explanatory power of the most commonly used asset pricing models by academics and practitioners. Analyses are conducted in the context of multiple forms of asset pricing frameworks. The chapter estimates three well-known asset pricing models, including the single factor classic CAPM, three-factor model by Fama and French (1993), and the four-factor model of Carhart (1997). This chapter is, to my knowledge, the first study to augment the newly established Fama and French (2015) five-factor asset pricing model with liquidity.[5] Finally, this chapter also provides evidence of the recent financial crisis's impact on liquidity and stock return. I do this by analysing two

[5] Florackis, Gregoriou, and Kostakis (2011) only use a four factor asset pricing model augmented with liquidity including the market, size, value, and momentum factors.

subsamples, including pre-financial crisis (1997 to 2007) and post-financial crisis (2008 to 2017). The results establish that the stock illiquidity level is higher in the pre-crisis period compared to the post-crisis period, and the difference between the top and bottom portfolios is statistically significant. However, the relationship between liquidity and stock return is only statistically significant for the pre crises period. The result could be attributed to the change in financial regulation in order to reduce the liquidity risk in the post-crisis period. After the global credit crunch financial crisis between 2007-2009, the Securities and Exchange Commission (SEC) released 2010 Reforms that adopted amendments to certain rules that govern money market funds in order to make assets more resilient to certain short-term market risks. The aim of the new rules is to improve the quality of portfolio securities and tighten the risk for the financial system[6]. Following Duffie (2018), financial regulations have been set to reduce the likelihood and severity of future financial turmoil. In particular, they focus on "four core elements" including making financial institutions more resilient, ending "too-big to fail", making derivatives markets safer and transforming shadow banking[7].

The remainder of the chapter is organized as follows: Section 3.2 reviews the literature on liquidity and asset prices. Section 3.3 describes the liquidity measures used in this chapter, including the RtoV, RtoTR, and RtoTRF ratios. Section 3.4 presents the data and summary statistics as well as the construction of the decile portfolios. The empirical time-series and cross-sectional results are reported in Sections 3.5 and 3.6, respectively. Finally, Section 3.7 concludes the chapter.

[6] https://www.sec.gov/rules/final/2010/ic-29132fr.pdf

[7] See Duffie (2018) for more details.

### 3.2 Literature Review

Over the last three decades, although numerous studies have been carried out to explain the role of liquidity in asset pricing, different conclusions are obtained about liquidity's importance when different liquidity proxies are employed. On the one hand, it is argued that more liquid securities tend to be held with shorter investment horizons, and they require lower expected returns. For instance, Amihud and Mendelson (1986b), using the bid-ask spread, which is defined as the difference between the bid and ask price as a liquidity proxy, provide evidence that there is a positive relationship between the bid-ask spread and market expected return. Focusing on US equities, Brennan, Chordia, and Subrahmanyam (1998) also provide evidence that liquidity is correlated negatively on required asset returns when employing dollar trading volume to measure liquidity. In particular, they find a statistically significant correlation between dollar volume and asset return on the NYSE and AMEX stock exchanges. Supporting evidence is seen in other studies when using samples from other stock markets such as the Australia market (Chan and Faff, 2005), emerging markets (Bekaert, Harvey, and Lundblad, 2007), and the Hong Kong market (Lam and Tam, 2011).

On the other hand, some empirical studies have shown conflicting evidence. For instance, Bekaert, Harvey, and Lundblad (2007) suggest that turnover ratio, which is considered as a proxy for liquidity as it captures the trading frequency dimension, does not significantly predict future return. Chordia, Subrahmanyam, and Anshuman (2001) also study whether expected stock return correlates to trading activity, which is another liquidity measure. They discover a strong and negative relation between stock return and the volatility of trading volume and share turnover. Furthermore, Eleswarapu and Reinganum (1993) suggest a seasonal effect because the bid-ask spread and average return are positively correlated to each other merely in January. Meanwhile, Hasbrouck (2009) proposes a new estimation of the trading effective cost from daily closing prices and finds mixed evidence when examining the relationship between their trading cost and stock return. In particular, he shows that the effective cost has a positive association to stock return, with the strongest relationship occurring in January.

In terms of asset pricing, numerous models, both single and multiple factors, are developed to deal with asset choice under risk conditions. As a result, different asset models are used in empirical studies in order to explain the relationship between liquidity and asset returns. Some widely used asset pricing models are the single factor CAPM, the three-factor model of Fama and French (1993) (hereby 3FF model), and the four-factor model of Carhart (1997). In CAPM, the expected stock return is related to the value of the security market. Fama and French (1993) expand the factors used to explained stock return by including size and book-to-market value to the asset pricing model. Meanwhile, the four-factor model of Carhart (1997) accounts for these three factors and the momentum factor. As the explanatory powers of asset pricing models are not the same, and there is a lack of investigation in research applications of these models, we apply four different model frameworks on my empirical data. They include the above three well-known asset pricing models and a new proposed model by Fama and French (2015) known as the five-factor model (5FF model). Besides some common risk factors such as the market, size, and value, the 5FF model captures two more patterns namely profitability and investment. Fama and French (2015) provide evidence that the five-factor model outperforms the three-factor model of Fama and French (1993) in reflecting the average security return.

### 3.3 Liquidity measures

This chapter mainly focuses on three alternative price impact ratios, namely the return to volume ratio by Amihud (2002), the return to turnover ratio developed by Florackis, Gregoriou, and Kostakis (2011) and the free-float adjusted price impact ratio by Karim et al. (2016).

*3.3.1 Return to volume ratio by Amihud (2002) – RtoV ratio*

The illiquidity ratio proposed by Amihud (2002) is the most commonly used price impact measure of liquidity in the finance literature. In particular, the illiquidity ratio also known as the return to volume ratio reflects the sensitivity of average absolute daily price to $1 trading volume for a stock. The average daily impact over a sample period is calculated as follows:

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{Dvol_{idt}} \tag{3.1}$$

where $RtoV_{it}$ is the return to volume ratio of stock i in the period t, $D_{it}$ is the number of total trading days in the period t for stock i, $R_{idt}$ is the return of stock i at day d, and $Dvol_{idt}$ is the dollar volume of stock i at day d in the period t. The stock is considered to be illiquid if the return to volume RtoV ratio is high.

In spite of the fact that the Amihud (2002) ratio is a useful and convenient proxy for liquidity, there are still some limitations to using this ratio. First, it carries a size bias. Cochrane (2005) argues that for two stocks with the same turnover, the stock with large market capitalization is automatically less illiquid than small stocks because they have lower Amihud ratio levels. As a result, the illiquidity ratio is incomparable across stocks with different market capitalizations (Florackis, Gregoriou, and Kostakis, 2011). Florackis, Gregoriou, and Kostakis (2011) also argue that it fails to reflect the trading frequency aspect of liquidity.

*3.3.2 Return to turnover ratio by Florackis, Gregoriou, and Kostakis (2011) – RtoTR ratio*

Florackis, Gregoriou, and Kostakis (2011) develop another price impact ratio to measure stock liquidity, known as the return to turnover ratio. It is considered as an alternative method to the widely used return to volume ratio in Amihud (2002). Using cross-sectional asset pricing tests, Florackis, Gregoriou, and Kostakis (2011) argue that the Amihud ratio comes with two major shortcomings. First, it contains a size bias as this ratio does not capture the difference in market capitalization across stocks. Second, the information about trading frequency is not considered in this return to volume ratio.

Florackis, Gregoriou, and Kostakis (2011) introduce a new liquidity proxy that captures the price impact dimension, which is calculated as the absolute stock return to its turnover ratio.

$$RtoTR_{it} = \frac{1}{D_{it}}\sum_{d=1}^{D_{it}}\frac{|R_{idt}|}{TR_{idt}} \tag{3.2}$$

where $RtoTR_{it}$ is the return to turnover ratio of stock i over the period of time t, $TR_{itd}$ is the turnover ratio calculated as the ratio of share traded over share outstanding of stock i at day d, $D_{it}$ and $R_{itd}$ are defined as in equation (1).

Compared to the Amihud ratio, the dollar trade volume in the denominator is substituted by share turnover ratio in the RtoTR ratio. The Florackis, Gregoriou, and Kostakis (2011) return to turnover ratio is free of size bias and captures trading frequency.

*3.3.3 Free-float Adjusted Price Impact Ratio by Karim et al. (2016) – RtoTRF ratio*

Recently, a new price impact ratio that considers the percentage of shares that are traded to public investors (i.e. free float factor) is introduced by Karim et al. (2016). It is defined as below:

$$RtoTRF_{it} = \frac{1}{D_{it}}\sum_{d=1}^{D_{it}}\frac{|R_{idt}|}{TRF_{idt}} \tag{3.3}$$

where $RtoTRF_{it}$ is the free float adjusted price impact ratio of stock i in period t, $TRF_{itd}$ is the turnover ratio adjusted with public free float factor of stock i in period t, $D_{it}$and $R_{itd}$ are defined in equation (1).

Compared to the RtoV and RtoTR ratios, the price impact ratio of Karim et al. (2016) is not only free of size bias and captures the effect of trading frequency, but it also reflects the real supply of available shares available to the public for trading.

## 3.4 Data and Summary Statistics

*3.4.1 Data selection*

The data samples for my investigation on stock liquidity and asset pricing for the US market are collected from the Centre for Research in Security Prices (CRSP) database and Thomson

DataStream. I obtain data on all public firms whose stocks are traded on three major US stock exchanges, including NYSE, AMEX, and NASDAQ exchanges, over the 21-year period from 1997 to 2017. This chapter considers all common stocks (CRSP share codes are 10 and 11), including both listed and de-listed assets to avoid the issue of survivorship bias.

For each stock, I collect daily data on share price, return, trading volume, and shares outstanding from the CRSP database. The free float factor (the percentage of common shares outstanding that are available for trading on the stock exchanges) and price to book ratio are obtained daily from Thomson DataStream. I then merge daily data from CRSP with data from DataStream using the CUSIP number[8]. Given that the free float factor of public US firms is only available daily in DataStream from January 1996, the sample period begins in 1996. Moreover, monthly data on the risk-free rate, market return, and risk factors including size, value, momentum, profitability, and investment for asset pricing models are obtained directly from the Kenneth R. French website[9].

Following Acharya and Pedersen (2005) and Pastor and Stambaugh (2003), I employ some filter criteria on my sample to remove outliers and reduce the measurement errors. In particular, we exclude stocks with daily share price below $5 and more than $1000. Moreover, a stock kept in the sample must have at least 15 daily observations in a month, and its market value must be a minimum of $10 million. I also exclude stocks with a zero free float number.

*3.4.2 Monthly data and portfolio construction*

In line with prior studies on asset pricing, this chapter use portfolios to test the correlation between expected stock returns and stock liquidity. Using portfolio levels are less affected by

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[8] CUSIP number stands for Committee on Uniform Securities Identification Procedures. It consists of nine characters and uniquely identifies a company or financial instrument (https://sec.gov).

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

noise and outliers than individual stocks (Patton and Timmermann, 2007). In particular, following Nguyen et al. (2007), stocks are sorted into 25 portfolios based on the ascending order of liquidity measures (RtoV, RtoTR, and RtoTRF ratios). At the end of month t-1, stocks are classified in 25 portfolios according to their liquidity value. Stocks with the lowest price impact ratio are included in portfolio 1 (P1), and portfolio 25 (P25) contains the stocks with the highest ratio. As these measures capture price impact dimension of liquidity, a higher ratio means a higher illiquid. As a result, P1 includes the most liquid stocks whereas the least liquid stocks are grouped in P25. In order to avoid confusion among high/low liquidity portfolio with low/high price impact ratio portfolio, this chapter refers to $P_{HIGH}$ for P1 and $P_{LOW}$ for P25. For robustness, both monthly equal-weighted and value-weighted portfolio returns are calculated. Portfolios are rebalanced on a monthly basis. Other monthly variables (liquidity, market value, and price to book) are calculated as the monthly average of their daily values. We also exclude months with less than 25 firms. The final sample consists of 4051 firms, 252 months in the 21-year period from Jan 1997 to Dec 2017. It is common practice to sort stocks into 25 portfolios in financial empirical research (see among others, Acharya and Pedersen, 2005, and Bali et al., 2014).

Four models are considered for the asset pricing test in this chapter. The first model is the single factor classic CAPM which captures the market factor. The second model is the Fama and French three-factor model (Fama and French, 1993), which accounts for the market, size and value factors. The third model is the Carhart four-factor model (Carhart, 1997), which includes the three risk factors of the 3FF model and adds the momentum factor. The last model is the five-factor model introduced by Fama and French (2015), which consists of the 3FF model with profitability, and investment as additional factors. The first three models are used widely in the asset pricing empirical studies, whereas the five factor model is still quite new and we are one of the first studies to implement this model in asset pricing.

*3.4.3 Descriptive Statistics*

Table 3.1, Panel A reports summary statistics of the main variables in my sample over the time period of 1997 to 2017, while Panel B shows Spearman rank correlation between them. Together with the three liquidity measures, we show the statistics for stock return (%), market capitalization, (MV) which is calculated by multiplying the share price and number of share outstanding, and the ratio of market value over book value of stock- price to book ratio (PTB).

The mean and median values of return to volume over the 21-year period are 0.539 and 0.005, respectively. Meanwhile, the figures of RtoTR and RtoTRF ratios are larger with mean values being 2.578 and 1.925, respectively, and median values being 0.352 and 0.281, respectively. I also report the statistics for these variables on the two sub-periods in Table 3.1 Panel B and Panel C. Generally, the median of illiquidity ratios of the pre-financial crisis (Feb 1997 to Dec 2007) are higher than that of the post-financial crisis period (Jan 2008 to Dec 2017). According to the Spearman rank correlation shown in Table 3.1, it is clear that three price impact ratios, including the return to volume (RtoV), the return to turnover (RtoTR), and the free float adjusted price impact ratio (RtoTRF) have strong and significant correlations together with the coefficients between them being more than 0.800. This is no surprise as these measures capture the price impact dimension of liquidity. Moreover, RtoV ratio is highly and strongly correlated with market capitalization at -0.947. The RtoTR and RtoTRF ratios show smaller correlation coefficients with market value (-0.686 and -0.666 respectively).

The basic approach of the chapter is sorting all stocks to decile portfolios based on the level of price impact ratios. In particular, at month t-1, according to ascending order of each liquidity measure, stocks are sorted and classified into 25 decile portfolios. Groups of stocks with the lowest price impact ratio are assigned in portfolio 1 (P1), while the highest ratio stocks are included in portfolio 25 (P25). Put in other words, P1 covers the most liquid stocks (PHIGH) whereas P25 includes the least liquid stocks (PLOW). Once the stocks are assigned to their portfolios, the 1 month-post ranking return will be calculated for each decile portfolio at month t. Through comparing the performance of the least liquid and most liquid portfolios, this chapter provides evidence of liquidity premium. For robustness, both equal weighted and value weighted portfolio returns are obtained. Portfolios are rebalanced on a monthly basic.

## Table 3.1: Summary Statistics

This table shows the descriptive statistics and Spearman rank correlations for the main variables used in my empirical study. *RtoV* is return to volume ratio, *RtoTR* is return to turnover ratio, and *RtoTRF* is the free float price impact ratio. *MV* is market capitalization, reported in million. *PTB* is price to book ratio calculated as the market value over book value of asset. *Ret* is the monthly stock return in percentages. Std.Dev is standard deviation. *, **, ***, denote statistical significant at the 10%, 5%, and 1% level, respectively.

**Descriptive Statistics**

| | *RtoVx10^6* | *RtoTR* | *RtoTRF* | *MV ($m)* | *PTB* | *Ret (%)* |
|---|---|---|---|---|---|---|
| **Panel A: Feb 1997 to Dec 2017** | | | | | | |
| Mean | 0.539 | 2.578 | 1.925 | 4837.297 | 2.825 | 1.417 |
| Median | 0.005 | 0.352 | 0.281 | 593.816 | 1.922 | 0.776 |
| Std.Dev | 2.389 | 8.800 | 6.400 | 20200.000 | 3.861 | 12.858 |
| **Panel B: Feb 1997 to Dec 2007** | | | | | | |
| Mean | 0.442 | 2.400 | 1.925 | 4042.821 | 2.940 | 1.485 |
| Median | 0.009 | 0.500 | 0.400 | 472.045 | 2.061 | 0.671 |
| Std.Dev | 1.829 | 7.000 | 5.200 | 19100.000 | 3.647 | 13.211 |
| **Panel C: Jan 2008 to Dec 2017** | | | | | | |
| Mean | 0.637 | 2.700 | 2.000 | 5656.745 | 2.704 | 1.346 |
| Median | 0.003 | 0.300 | 0.200 | 762.476 | 1.750 | 0.894 |
| Std.Dev | 2.851 | 10.300 | 7.400 | 21300.000 | 4.068 | 12.477 |

**Spearman rank correlation**

| | *RtoV* | *RtoTR* | *RtoTRF* | *MV* | *PTB* |
|---|---|---|---|---|---|
| RtoV | 1.000 | | | | |
| RtoTR | 0.836*** | 1.000 | | | |
| RtoTRF | 0.865*** | 0.967*** | 1.000 | | |
| MV | -0.947*** | -0.686*** | -0.666*** | 1.000 | |
| PTB | -0.349*** | -0.287*** | -0.290*** | 0.346*** | 1.000 |

**Table 3.2: Performance and characteristics of decile portfolios constructed on the basic of RtoV, RtoTR, and RtoTRF ratios**

At month t-1, all stocks are sorted and classified into 25 decile portfolios based on the RtoV, RtoTR, and RtoTRF level, rrspectively. The stocks with lowest ratio are assigned to PHIGH, whereas portfolio PLOW contains the highest price impact ratio stocks. Portfolios are rebalanced monthly. I then calculate the equal weighted (EW) and value weighted (VW) return of each portfolio at month t (return for 1 post-ranking month). EW returns are obtained as the annualized average monthly returns of equal weighted portfolio returns. VW returns are the annualized average monthly returns of value weighted portfolio returns. MV is the average monthly market capitalization of all stocks in each decile portfolio, which is calculated by multiplying the share price and the number of share outstanding and it is reported in $million. PTB is the average of market value over book value of stocks in each sorted portfolio. CAPM beta is average stock's beta in each portfolio obtained using 36 month rolling window. T-test column shows the statistic of t-test for the difference of the spread between P25 and P1. *, **, ***, denote statistical significant at the 10%, 5%, and 1% level, respectively.

| | Portfolios based on RtoV level (1) | | | | Portfolios based on RtoTR level (2) | | | | Portfolios based on RtoTRF level (3) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Decile** | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH}$ - $P_{LOW}$ | t-test | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH}$ - $P_{LOW}$ | t-test | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH}$ - $P_{LOW}$ | t-test |
| ***Panel A: Feb 1997 to Dec 2017*** | | | | | | | | | | | | |
| EW returns (%p.a) | 11.806 | 25.987 | -14.181 | -1.699* | 28.135 | 4.588 | 23.547 | 3.142*** | 29.853 | 3.786 | 26.067 | 3.372*** |
| VW returns (%p.a) | 14.272 | 23.786 | -9.514 | -1.128 | 27.471 | 7.242 | 20.229 | 2.861** | 33.258 | 5.241 | 28.017 | 4.020*** |
| RtoV ratio | 0.02 | 6.58 | -6.561 | -9.201*** | 0.005 | 0.159 | -0.154 | -8.758*** | 0.004 | 0.115 | -0.11 | -8.580*** |
| MV (£m) | 72,808 | 55 | 72,753 | 12.330*** | 4,978 | 271 | 4,707 | 10.91*** | 4,101 | 324.961 | 3,776 | 9.670*** |
| PTB | 4.939 | 1.52 | 3.42 | 5.425*** | 3.391 | 1.755 | 1.636 | 11.41*** | 3.549 | 2.202 | 1.347 | 2.202** |
| CAPM beta | 1.029 | 0.490 | 0.539 | 17.33*** | 1.329 | 0.641 | 0.688 | 9.800*** | 1.335 | 0.624 | 0.712 | 10.83*** |
| ***Panel B: Feb 1997 to Dec 2007*** | | | | | | | | | | | | |
| EW returns (%p.a) | 11.617 | 26.248 | -14.632 | -1.108 | 29.058 | -0.553 | 29.611 | 3.320*** | 29.417 | -1.622 | 31.039 | 3.860*** |
| VW returns (%p.a) | 16.352 | 20.43 | -4.078 | -0.319 | 30.729 | 5.149 | 25.58 | 2.862** | 38.324 | 2.802 | 35.522 | 3.780*** |
| RtoV ratio | 0.035 | 5.399 | -5.364 | -16.86*** | 0.007 | 0.131 | -0.124 | -18.97*** | 0.007 | 0.097 | -0.09 | -13.34*** |
| MV (£m) | 63,115 | 42 | 63,073 | 14.61*** | 3,462 | 139 | 3,323 | 12.39*** | 2,799 | 141 | 2,658 | 9.810*** |
| PTB | 5.822 | 1.683 | 4.139 | 6.083*** | 3.762 | 2.04 | 1.721 | 8.034*** | 6.837 | 2.765 | 4.072 | 2.290** |
| CAPM beta | 1.059 | 0.513 | 0.545 | 14.06*** | 1.609 | 0.529 | 1.08 | -8.784*** | 1.533 | 0.506 | 1.028 | 9.553*** |
| ***Panel C: Jan 2008 to Dec 2017*** | | | | | | | | | | | | |
| EW returns (%p.a) | 12.074 | 25.751 | -13.677 | -1.293 | 26.623 | 12.856 | 13.766 | 1.261 | 28.275 | 10.991 | 17.283 | 1.545 |
| VW returns (%p.a) | 11.987 | 27.584 | -15.597 | -1.375 | 25.091 | 16.285 | 8.806 | 0.678 | 29.022 | 10.81 | 18.212 | 1.661 |
| RtoV ratio | 0.002 | 7.88 | -7.878 | -5.728*** | 0.002 | 0.22 | -0.217 | -6.441*** | 0.002 | 0.157 | -0.154 | -6.130*** |
| MV (£m) | 83,487 | 69 | 83,418 | 7.762*** | 5,732 | 266 | 5,466 | 9.628*** | 4,649 | 233 | 4,416 | 9.670*** |
| PTB | 3.968 | 1.34 | 2.629 | 2.527** | 3.126 | 1.399 | 1.727 | 10.250*** | 2.855 | 1.358 | 1.497 | 2.050* |
| CAPM beta | 1.008 | 0.686 | 0.322 | 2.747** | 1.266 | 0.716 | 0.549 | -5.314*** | 1.321 | 0.699 | 0.622 | 6.364*** |

Table 3.2 presents the performance and characteristics of the sorted portfolios classified by the RtoV, RtoTR, and RtoTRF ratios for the whole period from Feb 1997 to Dec 2017 and the two financial crises sub-periods. Panel A shows the performance of sorted portfolios constructed on the basis of the price impact value for the whole sample whereas Panel B and Panel C report the performance for the subsamples. Column (1) show the results for portfolios based on the return to volume ratio, the results for return to turnover ratio and free float adjusted ratio are shown in column (2) and (3), respectively. In order to save space, I only report the portfolio of interests including PHIGH and PLOW, the spread between PHIGH and PLOW, and the t-statistic of the spread.

Following column (1), when portfolios are sorted based on the RtoV ratio, the spread between PHIGH and PLOW is -14.181% p.a. (t=-1.699) for equally weighted portfolio returns, and -9.514% p.a. with t=-1.128 for value weighted portfolio returns. However, these figures are not statistically significant. Interestingly, the value of market capitalization strictly declines from more than 72800 million to 54 million when moving from PHIGH to PLOW. It suggests that high RtoV stocks have smaller market capitalization. Indeed, the return to volume ratio is highly negative and significantly correlated to the size factor. The value of the CAPM beta fluctuates between 0.490 in PLOW and 1.029 in PHIGH, and the spread PHIGH - PLOW is significant at 1% level with a numerical value of 0.539 (t=17.33). This finding suggests that stocks with a low RtoV ratio outperform the stocks with a high RtoV level.

Similar results are witnessed in column (1) Panel B and Panel C. However, the PHIGH- PLOW spread of equal-weighted return (EW return) in the first period has a larger magnitude than that of second period, whereas the opposite is true with value-weighted return (VW return). In particular, the spread of equal weight portfolio returns in the period from 1997 to 2007 is -14.632% p.a. (t=-1.108) and in the second sub-period is -13.677% p.a. (t=-1.293). The figures for spreads of value-weighted portfolio returns are -4.078% p.a. (t=-0.319) and -15.597% p.a.

(t=-1.375), respectively. Nevertheless, these spreads are not statistically significant. Strong and significant relationship between the return to volume ratio and market capitalization is robust using two sub-periods. The decrease of MV is seen in both periods when moving from PHIGH to PLOW. In addition, the pre-financial crisis period shows a higher RtoV level, which is consistent with the argument that stocks are less liquid before financial turmoil.

The corresponding results of decile portfolios formed on RtoTR and RtoTRF levels are presented in Columns (2) and (3), respectively. It is interesting that returns of sorted portfolios based on the RtoTR and RtoTRF ratios show an opposite trend from PHIGH to PLOW with the findings of the RtoV ratio. PHIGH portfolio, which includes the stocks with the lowest values of price impact ratios, has the highest portfolio returns, for both equal and value-weighted portfolio returns. The results reveal a monotonic decline in portfolios' returns from the most liquid decile (PHIGH) to the least liquid decile (PLOW).

In particular, column (2) reports the performance of portfolios constructed on the basis of the return to turnover value. The return difference between the most liquid (PHIGH) and least liquid (PLOW) portfolio is statistically significant for both equal and value weighted returns, in the entire sample and the pre-financial crisis period. For instance, the PHIGH to PLOW premium of equal weighted return is 23.547% p.a. (t=3.142) over the period between 1997 and 2017, and is 29.611% p.a. (t=3.320) in the first sub-period. The corresponding premium of value-weighted returns are 20.229% p.a. (t=2.861) and 25.580% p.a. (t=2.862), respectively. In terms of market capitalization and price to book ratio, both of them have a positive correlation to the liquidity level of stocks. Portfolio with the most liquid stocks (PHIGH) contains mid-size stocks whereas small stocks are present in the least liquid portfolio (PLOW). The largest stocks appear in the middle of 25 decile portfolios. This evidence supports Florackis, Gregoriou, and Kostakis (2011), that the trading frequency effect outperforms the transaction cost component.

It can be observed from Table 3.2, column (3) the performance and characteristics of portfolios formed on the level of the new price impact ratio- the RtoTRF ratio. The results of the whole sample are presented in Panel A. Similar trends are seen on the value-weighted and equal-weighted return when moving from the portfolio with the smallest RtoTRF ratio to the portfolio with the largest ratio. As shown in Panel A, Portfolio PHIGH has the highest average returns while the opposite is true with portfolio PLOW. The PHIGH - PLOW premium is 26.067% p.a. (t=3.372) for equal-weighted return and 28.017% p.a. (t=4.020) for the value-weighed return. Both of them are statistically significant. In terms of market capitalization, there is a decline of MV through PHIGH to PLOW, even though it is a non-monotonic relation. As a result, it suggests that size premium is not reflected in the spread of sorted RtoTRF portfolios.

Table 3.2, column (3) Panel B and Panel C show the corresponding results for the pre-financial crisis and post-financial crisis period. The portfolio's return decreases monotonically in both equal-weighted and value-weighted returns from the most liquid to the least liquid portfolio. However, the liquidity premium is only significant over the time from 1997 to 2007. It can be seen that the liquidity premium yielded in the post-financial crisis is smaller than the premium in the previous period. This finding is consistent with the suggestion of Ben-Rephael, Kadan, and Wohl (2015), that there is a strongly decrease in characteristic liquidity premium over the past four decades. They also argue that security liquidity has improved as a result of dramatic growth in trading activity. Supporting this argument, Baker, Cummings, and Jagtiani (2017) find evidence that the strengthened capital and liquidity requirements have contributed to a reduction in systemic risk, and enhanced financial stability in the post-crisis period. In terms of the price to book ratio, the characteristics of 25 decile portfolios also show that stocks with a greater RtoTRF ratio have a smaller PTB values

Overall, the above empirical analysis show that the return to volume ratio is highly correlated to size factor and suffers from a size bias. Moreover, sorted RtoTR and RtoTRF portfolio' returns show the opposite direction relative to portfolio's returns based on the RtoV ratio when moving from PHIGH to PLOW. This finding suggests that the correlation of liquidity and stock return is due to the combination effects of trading costs and trading frequency. However, the trading frequency component is not reflected in the RtoV price impact ratio. In addition, the return to turnover, and free float adjusted price impact ratio seem to be better than the RtoV in capturing the impact of trading frequency. These liquidity measures are also free of size bias.

### 3.5 Time- series asset pricing tests

In this section, I test the risk-adjusted performance of 25 sorted portfolios constructed based on the liquidity measures using asset pricing tests.

In order to conduct a thorough comprehensive econometric analysis, I examine the portfolio abnormal performance using four asset pricing models. They are the standard original single factor CAPM, Fama and French three-factor model, Carhart four-factor model, and the Fama and French five factor model[10]. The first model of modern asset pricing theory is the CAPM developed by Sharpe (1964) and Lintner (1965). According to the CAPM, the expected excess return of a security is a linear function of systematic or market risk.

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \varepsilon_{it} \tag{3.4}$$

where $R_{it}$ is the return of portfolio i in month t, $R_{ft}$ is risk-free rate return in month t, and $MKT_t$ is the market excess return that is obtained by subtracting the risk free rate from market

[10] Original asset pricing models depend on the usage of mimicking portfolios (replicating the risk factors). However, in this chapter I construct portfolios on the basis of the liquidity ratio in order to capture the risk-adjusted returns of portfolios. This approach is similar to other papers such as Imrohoruglu and Tuzel (2014), Liu (2009), and Pastor and Stambaugh (2003).

portfolio return in month t. The next model is the Fama-French three-factor model by Fama and French (1993). It captures the market, value and size factors.

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{it} \quad (3.5)$$

where $SMB_t$ stands for the size factor, $HML_t$ stands for the value risk factor. Other variables are defined as in equation (4). I also estimate the four-factor model by Carhart (1997) for asset pricing test with the following equation:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \varepsilon_{it} \quad (3.6)$$

where $MOM_t$ stands for the past performance factor (momentum). The last model I implement is the Fama and French five factor model – 5FF, introduced by Fama and French (2015).

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \varepsilon_{it} \quad (3.7)$$

where $RMW_t$ and $CMA_t$ stand for profitability and investments, respectively. In order to test the null hypothesis that all 25 alphas are jointly equal to zero, this chapter uses the multivariate test of Gibbons, Ross and Shanken (1989) (GRS test). This test is widely used in the asset pricing literature, for instance it is used among others by Pastor and Stambaugh (2003), Nguyen et al. (2007), and Grauer and Janmaat (2010).

**Table 3.3: Alpha value of value-weighted portfolio based on RtoV, RtoTR, and RtoTRF ratios**

This table shows the post-ranking alpha (%) of value-weighted decile portfolios constructed based on three price impact ratios. At month t-1, all stocks are sorted and classified into 25 decile portfolios based on the price impact ratio. PLOW contains the highest price impact ratio stocks whereas stocks with lowest ratio are assigned on PHIGH. The sorting procedure is at each month with all eligible stocks at that time. The excess sorted portfolio returns for one post ranking month are obtained as the post ranking portfolio return minus the monthly risk free rate. The alphas are estimated as intercepts from the regression of the asset pricing model. CAPM alpha is monthly alpha estimated from CAPM, 3FF alpha is monthly alpha obtained from Fama and French three-factor model, 5FF alpha is monthly alpha derived from Fama and French five-factor model, and Carhart alpha is monthly alpha estimated from Carhart four-factor model. PHIGH-PLOW is the difference of alphas between highest and lowest liquidity level portfolios. GRS test is the statistic of Gibbons, Ross, and Shanken (1989) test under the null hypothesis that all 25 portfolios' alphas jointly equal zero. *, **, ***, denotes statistical significant at the 10%, 5%, and 1% level, respectively.

| | Portfolios based on RtoV level (1) | | | | Portfolios based on RtoTR level (2) | | | | Portfolios based on RtoTRF level (3) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Decile** | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH} - P_{LOW}$ | **GRS-test** | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH} - P_{LOW}$ | **GRS-test** | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH} - P_{LOW}$ | **GRS-test** |
| ***Panel A: Feb 1997 to Dec 2017*** | | | | | | | | | | | | |
| CAPM alpha | 0.355 | 1.129 | -0.775 | | 1.274 | -0.058 | 1.461 | | 1.632 | -0.190 | 1.97 | |
| | 3.693*** | 4.997*** | -3.155*** | 7.93*** | 6.976*** | -0.27 | 4.794*** | 11.17*** | 8.629*** | -0.950 | 6.614*** | 11.8*** |
| 3FF alpha | 0.405 | 0.998 | -0.593 | | 1.29 | -0.199 | 1.605 | | 1.626 | -0.329 | 2.096 | |
| | 4.995*** | 4.846*** | -2.679*** | 11.26*** | 7.391*** | -1.100 | 5.924*** | 10.98*** | 9.028*** | -1.880* | 7.787*** | 11.6*** |
| Carhart alpha | 0.388 | 1.094 | -0.706 | | 1.275 | -0.164 | 1.55 | | 1.627 | -0.281 | 2.041 | |
| | 4.754*** | 5.388*** | -3.277*** | 13.13*** | 7.232*** | -0.900 | 5.678*** | 10.67*** | 8.932*** | -1.600 | 7.545*** | 11.3*** |
| 5FF alpha | 0.389 | 1.046 | -0.657 | | 1.349 | -0.237 | 1.701 | | 1.683 | -0.354 | 2.176 | |
| | 4.596*** | 4.876*** | -2.973*** | 9.71*** | 7.428*** | -1.260 | 6.066*** | 9.59*** | 9.006*** | -1.960** | 7.852*** | 10.2*** |
| ***Panel B: Feb 1997 to Dec 2007*** | | | | | | | | | | | | |
| CAPM alpha | 0.501 | 0.888 | -0.387 | | 1.583 | -0.141 | 1.724 | | 2.022 | -0.307 | 2.328 | |
| | 3.158*** | 2.847*** | -1.106 | 5.38*** | 4.649*** | -0.507 | 3.924*** | 6.27*** | 6.343*** | -1.046 | 5.376*** | 7.44*** |
| 3FF alpha | 0.654 | 0.552 | 0.103 | | 1.802 | -0.466 | 2.268 | | 2.172 | -0.704 | 2.876 | |
| | 5.004*** | 1.987** | 0.334 | 5.88*** | 5.725*** | -1.902 | 5.687*** | 5.73*** | 7.522*** | -2.81*** | 7.529*** | 7.08*** |
| Carhart alpha | 0.635 | 0.708 | -0.073 | | 1.813 | -0.400 | 2.213 | | 2.147 | -0.668 | 2.815 | |
| | 4.759*** | 2.577*** | -0.238 | 7.33*** | 5.626*** | -1.610 | 5.437*** | 5.95*** | 7.271*** | -2.616 | 7.210*** | 6.87*** |
| 5FF alpha | 0.614 | 0.566 | 0.048 | | 1.997 | -0.521 | 2.518 | | 2.379 | -0.767 | 3.146 | |
| | 4.568*** | 1.973** | 0.15 | 5.26*** | 6.311*** | -2.09** | 6.252*** | 5.23*** | 8.261*** | -3.00*** | 8.173*** | 6.77*** |
| ***Panel C: Jan 2008 to Dec 2017*** | | | | | | | | | | | | |
| CAPM alpha | 0.216 | 1.373 | -1.157 | | 1.261 | 0.522 | 0.739 | | 1.499 | 0.341 | 1.158 | |
| | 2.332** | 4.227*** | -3.43*** | 3.23*** | 5.624*** | 1.443 | 1.734* | 6.71*** | 6.206*** | 1.277 | 3.212*** | 6.81*** |
| 3FF alpha | 0.233 | 1.43 | -1.197 | | 1.209 | 0.528 | 0.681 | | 1.466 | 0.369 | 1.098 | |
| | 2.891*** | 4.603*** | -3.73*** | 8.00*** | 5.716*** | 1.532 | 1.683* | 6.84*** | 6.222*** | 1.467 | 3.186*** | 6.80*** |
| Carhart alpha | 0.23 | 1.437 | -1.207 | | 1.211 | 0.528 | 0.683 | | 1.471 | 0.369 | 1.102 | |
| | 2.950*** | 4.689*** | -3.82*** | 8.72*** | 5.730*** | 1.526 | 1.684* | 6.87*** | 6.274*** | 1.461 | 3.199*** | 6.73*** |
| 5FF alpha | 0.167 | 1.574 | -1.408 | | 1.223 | 0.734 | 0.489 | | 1.461 | 0.613 | 0.848 | |
| | 2.194** | 4.856*** | -4.23*** | 8.13*** | 5.489*** | 2.056** | 1.161 | 6.31*** | 5.952*** | 2.435** | 2.411** | 6.38*** |

For comparison purposes, results of portfolio's alpha value are reported for all three liquidity measures formed portfolios as shown in Table 3.3. First, Table 3.3, column (1) presents the value-weighted portfolio's alphas estimated under the four asset pricing models for portfolios constructed on the basis of the RtoV price impact ratio. Panel A shows the results for the whole period from 1997 to 2017, results of the two sub-periods are reported in Panel B and Panel C. Specifically, over the period form 1997-2017, It can be seen that none of the four asset pricing models can account for the liquidity premium by the return to volume ratio. All four alphas of the $P_{HIGH}$-$P_{LOW}$ spread are negative and statistically significant. The CAPM alpha is -0.775% per month (t=-3.155) and the three factor Fama and French alpha is -0.593% per month (t=-2.679). The alpha values of the five factor Fama and French model and Carhart four factor model have similar figures. For the sub-periods, the post-financial crisis period from Jan 2008 to Dec 2017 shows a similar trend on the alpha value of the P1-P25 spread but with greater magnitude. Interestingly, as shown in Table 3.5 Panel B, which refers to the pre-financial crisis period, the difference in alpha values of P1 and P25 for all four asset pricing models are not statistically significant.

The corresponding alpha value of portfolios sorted on the RtoTR and RtoTRF price impact ratios are presented in Table 3.3 column (2) and (3), respectively. There is a similar movement between RtoTR and RtoTRF sorted portfolio alphas when moving from $P_{HIGH}$ to $P_{LOW}$. Portfolios with the smallest levels of liquidity measure ($P_{HIGH}$) yield the highest estimated alpha, whereas $P_{LOW}$ with biggest level of price impact ratio experiences the lowest alpha value. However, portfolios constructed on the free float adjusted price impact ratio display a greater alpha value, compared to the return to turnover sorted portfolios. In particular, Table 3.3 column (2) shows the value-weighted alpha value of portfolios formed on the RtoTR ratio. As shown in Panel A, all four alphas of the $P_{HIGH}$-$P_{LOW}$ spread computed with respect to different factors of asset pricing models are positive and statistically significant. CAPM adjusted premium is lowest with 1.461% per month (t=4.794), the highest premium belongs to the five factor Fama and French model (1.701% per month with t=6.066). Similar results are seen in Panel B when using the sample from 1997 to 2007 but with higher subsample alphas. For example, the five factor Fama and French alpha value of the PHIGH-PLOW spread is 2.518% per month (t=6.252). Nevertheless, in the later sub-period, the asset pricing models cannot completely account for RtoTR premium, as alpha value of the PHIGH-PLOW spread obtained from these models are positive but only significant at the 10% level, except for the 5FF alpha. For instance, CAPM alpha of PHIGH-PLOW spread is 0.739% per month (t=1.734) whereas the corresponding alpha of 3FF model is 0.681% per month (t=1.683). The 5FF premium yielded by the PHIGH-PLOW difference is positive at 0.489% per month but not statistically significant (t=1.161).

Table 3.3 column (3) reports the value weighted alpha of portfolios formed on the RtoTRF ratio. It is clear that neither CAPM nor 3FF, four-factor model or 5FF can completely account for the risk adjusted performance. Indeed, Panel A shows that the liquidity premiums are positive and significant at the 1% level under four different asset pricing models. The CAPM adjusted return on the most liquid portfolio is 1.632% per month (t= 8.629) and the figure for the least liquid portfolio is -0.190% per month (t=-0.950). It leads to a high and significant liquidity premium of 1.970% per month (t=6.614). The Fama and French three factor and four factor Carhart premiums are greater than 2% per month. The Fama and French five factor model yields the highest alpha of the PHIGH-PLOW spread with 2.176% per month (t=7.852). The results are also robust across the two financial crises sub-periods. Specifically, the pre-crises period experiences greater alpha values compared to the post-crises period.

In term of the GRS test, the null hypothesis that the 25 estimated alphas are jointly equal to zero is rejected at the 1% significance level, over the entire sample period for four asset pricing models considered, when using three liquidity measures to construct portfolios. These findings support the argument that abnormal returns yielded from 25 decile portfolios constructed on the basis of three price impact ratios cannot be accounted completely by the asset pricing models.

Overall, the evidence provided in Section 3.4 and Section 3.5 has implied that the free float adjusted price impact ratio RtoTRF and the return to turnover ratio – RtoTR, are superior to the return to volume ratio – RtoV. This is because they both capture the impact of trading frequency on liquidity, and the RtoTRF ratio accounts for the real supply of available stocks to the public for trading. The premiums of the portfolio formed on the basis of the RtoTRF ratio are positive and significant using data on the US market between 1997 and 2017. This finding is robust when considering two sub-samples including pre and post financial crises periods. It suggests that stocks with higher liquidity levels offer higher expected returns. In addition, the RtoTR ratio's performance strongly supports the finding of Florackis, Gregoriou, and Kostakis (2011), that the trading cost effect is dominated by the impact of trading frequency. Equities with low transaction costs may still get the high premium if they are traded more frequency. Moreover, the finding of significant portfolios' alphas also shows that widely used asset pricing models cannot account for the entire abnormal returns yielded by liquidity measures.

For robustness, I also calculate alphas for equal-weighted portfolios constructed on the basis of the three price impact ratios. Tables 3.4 columns (1), (2), and (3) show similar results for equal-weighted alphas of decile portfolios based on RtoV, RtoTR, and the RtoTRF price impact ratios, respectively. For example, the equal-weighted alpha of portfolios constructed on RtoTR ratios in Table 3.4 column (2) show a similar trend compared to value-weighted alpha (Table 3.3 column (2)). However, the difference in alphas between $P_{HIGH}$ and $P_{LOW}$ in the post-crisis period are stronger because they are significant at the 5% level for the first three asset pricing models, and at the 10% level for the five-factor Fama and French model. The equal-weighted alpha of portfolios formed on the RtoTRF ratio are reported in Table 3.4 column (3). CAPM alpha value declines significantly from 1.385% per month (t=8.368) in $P_{HIGH}$ to -0.035% per month (t=-1.706) in $P_{LOW}$. This leads to a positive and significant $P_{HIGH}$ – $P_{LOW}$ premium at 1.716% per month (t=6.731). Lowest $P_{HIGH}$ – $P_{LOW}$ spread premium are viewed in the Fama and French five-factor model. This finding is robust across two sub financial crises periods as shown in Panel B and Panel C of Table 3.4 column (3).

**Table 3.4: Alpha value of equal-weighted portfolio based on RtoV, RtoTR, and RtoTRF ratios**

This table shows the post-ranking alpha (%) of value-weighted decile portfolios constructed based on three price impatc ratios. At month t-1, all stocks are sorted and classified into 25 decile portfolios based on the price impact ratio. PLOW contains the highest price impact ratio whereas stock with lowest ratio are assigned on PHIGH. The sorting procedure is at each month with all eligible stocks at that time. The excess sorted portfolio returns for one post ranking month are obtained as the post ranking portfolio return minus the monthly risk free rate. The alphas are estimated as intercepts from the regression of asset pricing model. CAPM alpha is monthly alpha estimated from CAPM, 3FF alpha is monthly alpha obtained from Fama and French three-factor model, 5FF alpha is monthly alpha derived from Fama and French five-factor model, and Carhart alpha is monthly alpha estimated from Carhart four-factor model. PHIGH-PLOW is the difference of alphas between highest and lowest liquidity level portfolios. GRS test is the statistic of Gibbons, Ross, and Shanken (1989) test under the null hypothesis that all 25 portfolios' alphas jointly equal zero. *, **, ***, denotes statistical significant at the 10%, 5%, and 1% level, respectively.

| | Portfolios based on RtoV level (1) | | | | Portfolios based on RtoTR level (2) | | | | Portfolios based on RtoTRF level (3) | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Decile | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH}$ – $P_{LOW}$ | GRS-test | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH}$ – $P_{LOW}$ | GRS-test | $P_{HIGH}$ | $P_{LOW}$ | $P_{HIGH}$ – $P_{LOW}$ | GRS-test |
| ***Panel A: Feb 1997 to Dec 2017*** | | | | | | | | | | | | |
| CAPM alpha | 0.113 | 1.303 | -1.19 | | 1.305 | -0.283 | 1.588 | | 1.385 | -0.331 | 1.716 | |
| | 1.592 | 6.046*** | -5.24*** | 7.34*** | 8.085*** | -1.445 | 6.259*** | 6.49*** | 8.368*** | -1.706* | 6.731*** | 6.75*** |
| 3FF alpha | 0.143 | 1.187 | -1.044 | | 1.206 | -0.423 | 1.628 | | 1.281 | -0.472 | 1.753 | |
| | 2.11** | 6.035*** | -5.306*** | 7.89*** | 9.587*** | -2.521** | 7.769*** | 8.69*** | 10.033*** | -2.830*** | 8.346*** | 9.08*** |
| Carhart alpha | 0.138 | 1.309 | -1.172 | | 1.284 | -0.328 | 1.612 | | 1.388 | -0.387 | 1.775 | |
| | 2.00** | 6.887*** | -6.163*** | 10.39*** | 10.569*** | -2.007** | 9.868*** | 10.2*** | 11.706*** | -2.363** | 8.782*** | 10.5*** |
| 5FF alpha | 0.173 | 1.217 | -1.044 | | 1.146 | -0.395 | 1.541 | | 1.226 | -0.45 | 1.676 | |
| | 2.46** | 5.943*** | -4.824*** | 6.72*** | 1.146 | -0.395 | 7.061*** | 7.18*** | 9.241*** | -2.590*** | 7.665*** | 7.61*** |
| ***Panel B: Feb 1997 to Dec 2007*** | | | | | | | | | | | | |
| CAPM alpha | 0.127 | 1.264 | -1.137 | | 1.45 | -0.623 | 2.073 | | 1.508 | -0.703 | 2.211 | |
| | 1.155 | 4.071*** | -3.452*** | 2.37** | 5.366*** | -2.511** | 5.651*** | 5.08*** | 5.738*** | -2.878*** | 6.163*** | 4.62*** |
| 3FF alpha | 0.185 | 0.942 | -0.757 | | 1.311 | -0.93 | 2.241 | | 1.378 | -1.019 | 2.397 | |
| | 1.699* | 3.424*** | -2.561** | 2.48** | 6.578*** | -4.403 | 7.718*** | 8.35*** | 7.159*** | -4.922*** | 8.479*** | 6.95*** |
| Carhart alpha | 0.184 | 1.138 | -0.954 | | 1.467 | -0.794 | 2.26 | | 1.56 | -0.883 | 2.443 | |
| | 1.657* | 4.267*** | -3.302*** | 3.68*** | 7.679*** | -3.84*** | 8.029*** | 10.7*** | 8.742*** | -4.363*** | 9.053*** | 8.34*** |
| 5FF alpha | 0.202 | 0.917 | -0.714 | | 1.292 | -0.934 | 2.225 | | 1.368 | -1.021 | 2.389 | |
| | 1.807* | 3.223*** | -2.336** | 2.44** | 6.261*** | -4.30*** | 7.427*** | 7.62*** | 6.877*** | -4.803*** | 8.206*** | 6.41*** |
| ***Panel C: Jan 2008 to Dec 2017*** | | | | | | | | | | | | |
| CAPM alpha | 0.13 | 1.334 | -1.203 | | 1.35 | 0.501 | 0.848 | | 1.411 | 0.369 | 1.042 | |
| | 1.717* | 4.469*** | 3.901*** | 1.97* | 5.756*** | 1.857* | 2.372** | 3.76*** | 6.277*** | 1.364 | 2.961*** | 3.16*** |
| 3FF alpha | 0.129 | 1.368 | -1.239 | | 1.348 | 0.538 | 0.81 | | 1.402 | 0.406 | 0.997 | |
| | 1.789* | 4.759*** | -4.180*** | 3.32*** | 6.896*** | 2.081** | 2.500** | 5.03*** | 7.313*** | 1.555 | 3.079*** | 4.79*** |
| Carhart alpha | 0.128 | 1.378 | -1.25 | | 1.356 | 0.543 | 0.813 | | 1.412 | 0.409 | 1.002 | |
| | 1.78* | 4.993*** | -4.384*** | 3.53*** | 7.288*** | 2.113** | 2.563** | 5.87*** | 7.965*** | 1.574 | 3.184*** | 5.62*** |
| 5FF alpha | 0.099 | 1.579 | -1.48 | | 1.305 | 0.719 | 0.586 | | 1.375 | 0.615 | 0.76 | |
| | 1.342 | 5.380*** | -4.891*** | 3.92*** | 6.383*** | 2.718*** | 1.753* | 4.61*** | 6.802*** | 2.326** | 2.283** | 4.70*** |

### 3.6 Cross-sectional asset pricing test

In this section, I provide detailed evidence of the cross-sectional variation in portfolio's return. In particular, I would like to examine how these returns vary over time and across deciles. Section 3.5 analyses the time-series abnormal performance of portfolios' returns, which are constructed on the basis of one of three price impact ratios including the RtoV, RtoTR, and RtoTRF ratios. Therefore, it is expected that a price impact factor can be added to the traditional asset pricing models to explain these anomalies. Following Florackis, Gregoriou, and Kostakis (2011), a price impact factor (PI) defined as the difference in value weighted return between portfolio $P_{HIGH}$ and portfolio $P_{LOW}$ is included in the asset pricing models described in Section 3.5. This section will test whether PI has a positive and significant effect on portfolios' returns.

I conduct cross sectional empirical analysis using the Fama-MacBeth (1973) regression technique. First, based on monthly data, the betas are computed as the estimation from the time-series regression of excess portfolio's return on a set of risk factors corresponding with the four asset pricing models explained in the previous Section. Generally, it comes with below form:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,j} X_{j,t} + \beta_{i,PI} PI_t + \varepsilon_{it} \qquad (3.8)$$

Where $R_{it}$ is the return of portfolio i at month t, $R_{ft}$ is the monthly risk free rate return at month t, $X_{j,t}$ is a set of explanatory variables including risk factors in each asset pricing model. These factors are collected monthly from Kenneth French's website. $PI_t$ represents the monthly price impact factor at month t as previously defined. The regression (3.8) is run for each of the 25 decile portfolios using a rolling window of 36 months. I then estimate a cross-sectional regression across 25 deciles for each month t using the following model:

$$R_{it} - R_{ft} = \gamma_{0,t} + \gamma_{j,t}\hat{\beta}_{j,t} + \gamma_{PI,t}\hat{\beta}_{PI,t} + \omega_{it} \qquad (3.9)$$

where $\gamma$ (gamma) represents the risk premium coefficients associated with each beta. $\hat{\beta}_{j,t}$ is the corresponding beta estimated from equation (3.8) for each explanatory variable X, $\hat{\beta}_{PI,t}$ is the estimated beta of the price impact factor (PI) from the above time-series regression. The estimated coefficients are reported as the average of the time-series coefficients, which is given by:

$$\gamma_j = \sum_{t=1}^{T} w_{j,t}\gamma_{j,t} \tag{3.10}$$

Where $\gamma_{j,t}$ is the cross-sectional regression estimate of $\gamma_j$ in month t, and $w_{j,t}$ is the weight for $\gamma_{j,t}$. Following Fama and MacBeth (1973) I have equal weighting (i.e.,$w_{j,t} = 1/T$).

In order to account for heteroscedasticity and autocorrelation-consistent standard errors, the t-statistics are calculated using a Newey-West correction with two lags[11] (Newey and West 1987). This approach is used by other studies such as Imrohoroglu and Tuzel (2014), Lewellen (2015), and Liu (2009). I report the results for the single factor CAPM, 3FF, Carhart four factor, and 5FF.

Tables 3.5 and 3.6 show the results of the cross-sectional regression and associated t-statistic testing whether the average estimated coefficients equal zero. Table 3.5, Panel A presents results of the cross-sectional regression of value-weighted portfolios formed according to the RtoTRF ratio. The coefficients of price impact premiums are positive and significant when using all four asset pricing models. In particular, when PI is added into the single factor CAPM, the average monthly premium is 0.64% (t=2.56) and the figure is 7.68% per year (annual premiums are calculated as 12 times the monthly estimates). The estimated coefficients of $\gamma_{PI}$ remain positive and significant at the 1% level when adding PI into 3FF, Carhart and 5FF models with the figures being 0.82% (9.84% p.a), 0.83% (9.96% p.a), and 0.92% (11.04%

[11] I use a two lag structure in my analysis in line with the previous literature such as Lee, Ng, and Swaminathan (2009), and Roll, Schwartz, and Subrahmanyam (2010).

p.a), respectively. Similar results are seen in Table 3.5 Panel B when decile portfolios are sorted on the basis of the RtoTR price impact ratio. The coefficients of PI are positive and significant at the 1% level, except for the single factor CAPM, where significance is at the 5% level. In particular, PI-adjusted CAPM risk premium is 0.66% (t=2.53) or 7.9% per year. The level of monthly premium of 3FF, Carhart, and 5FF models are 0.84% (t=3.22), 0.82% (t=3.25), and 0.93% (t=3.71), respectively.

For completeness, I also run cross-sectional asset pricing tests with an alternative price impact factor (PI_alter). It is computed as the spread between portfolios' returns of (P1+P2)/2 and (P24 +P25)/2. The results are shown in Table 3.6. Using this alternative price impact factor, I obtain similar results for both the RtoTR and RtoTRF sorted portfolios. Specifically, the premium added by PI to all asset pricing models are positive and statistically significant when decile portfolios are sorted on the basic of the RtoTR and RtoTRF ratios. The highest levels of monthly premium belong to PI-adjusted 5FF model with the figures being 0.93% (t=3.71) and 0.92% (t=3.75), respectively.

Overall, the findings from the cross-sectional regression strongly support the argument that the price impact factor PI is priced. I also discover that the PI can help to explain the cross-sectional variation in returns of portfolios, which are formed according to the RtoTRF and RtoTR price impact ratios.

**Table 3.5: Cross-sectional asset pricing test.**

This table presents the average estimates of the risk premium of price impact factor and other variable coefficients obtained from two stage Fama and MacBeth cross-sectional regression, using monthly data of 25 value-weighted portfolios' returns (equation 9). The sample period is from 1997 to 2017. Decile portfolios are formed on the basis of each price impact ratio. Price impact factor (PI) is the spread between P1 and P25 (PHIGH-PLOW). PI is added to the traditional asset pricing model and then run using the cross-sectional regression. The process is repeated for four asset pricing models. *, **, ***, denote statistical significant at the 10%, 5%, and 1% level, respectively.

| | $\gamma_0$ | $\gamma_{MKT}$ | $\gamma_{PI}$ | $\gamma_{SMB}$ | $\gamma_{HML}$ | $\gamma_{MOM}$ | $\gamma_{RMW}$ | $\gamma_{CMA}$ | *Avg.R square* |
|---|---|---|---|---|---|---|---|---|---|
| ***Panel A: Decile portfolios based on RtoTRF*** | | | | | | | | | |
| CAPM & PI | 1.38 | -0.21 | 0.64 | | | | | | 21.53 |
| | *6.35**** | *-0.59* | *2.56*** | | | | | | |
| 3FF & PI | 1.29 | -0.2 | 0.82 | 0.13 | -0.35 | | | | 36.26 |
| | *5.50**** | *-0.53* | *3.38**** | *0.62* | *-1.12* | | | | |
| Carhart & PI | 1.3 | -0.24 | 0.83 | 0.04 | -0.35 | 0.29 | | | 41.42 |
| | *5.65**** | *-0.66* | *3.40**** | *0.21* | *-1.12* | *0.64* | | | |
| 5FF & PI | 1.41 | -0.32 | 0.92 | -0.04 | -0.25 | | 0.04 | -0.32 | 47.44 |
| | *6.12**** | *-0.87* | *3.75**** | *-0.19* | *-0.82* | | *0.18* | *-1.54* | |
| ***Panel B: Decile portfolios based on RtoTR*** | | | | | | | | | |
| CAPM & PI | 1.32 | -0.12 | 0.66 | | | | | | 19.5 |
| | *5.87**** | *-0.32* | *2.53*** | | | | | | |
| 3FF & PI | 1.13 | 0.02 | 0.84 | 0.1 | -0.51 | | | | 34.58 |
| | *5.07**** | *0.04* | *3.22**** | *0.45* | *-1.69* | | | | |
| Carhart & PI | 1.12 | -0.02 | 0.82 | 0.05 | -0.5 | 0.43 | | | 40.77 |
| | *4.92**** | *-0.05* | *3.25**** | *0.24* | *-1.63* | *0.96* | | | |
| 5FF & PI | 1.07 | 0.04 | 0.93 | 0.12 | -0.48 | | -0.03 | -0.33 | 45.72 |
| | *4.68**** | *0.11* | *3.71**** | *0.53* | *-1.53* | | *-0.1* | *-1.61* | |

**Table 3.6: Cross- sectional asset pricing test for alternative price impact factor.**

This table presents the average estimates of the risk premium of price impact factor and other variable coefficients obtained from two stage Fama and MacBeth cross-sectional regressions using monthly data of 25 value-weighted portfolios' returns (equation 9). The sample period is from 1997 to 2017. Decile portfolios are formed on the basis of each price impact ratio. Price impact factor (PI_alter) is the spread between (P1+P2)/2 and (P24+P25)/2. PI is added to the traditional asset pricing model and then run using the cross-sectional regression. The process is repeated for four asset pricing models. Avg.$R^2$ is the time-series average R-squared from monthly regressions. The t-statistics are reported in italic below the estimated coefficients. *, **, ***, denote statistical significant at the 10%, 5%, and 1% level, respectively.

| | $\gamma_0$ | $\gamma_{MKT}$ | $\gamma_{PI\_alter}$ | $\gamma_{SMB}$ | $\gamma_{HML}$ | $\gamma_{MOM}$ | $\gamma_{RMW}$ | $\gamma_{CMA}$ | *Avg.* $R^2$ |
|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Decile portfolios based on RtoTRF ratio* | | | | | | | | | |
| **CAPM & PI** | 1.38 | -0.21 | 0.64 | | | | | | 21.53 |
| | *6.35**** | *-0.59* | *2.56*** | | | | | | |
| **3FF & PI** | 1.29 | -0.20 | 0.82 | 0.13 | -0.35 | | | | 36.26 |
| | *5.50**** | *-0.53* | *3.38**** | *0.62* | *-1.12* | | | | |
| **Carhart & PI** | 1.30 | -0.24 | 0.83 | 0.04 | -0.35 | 0.29 | | | 41.42 |
| | *5.65**** | *-0.66* | *3.40**** | *0.21* | *-1.12* | *0.64* | | | |
| **5FF & PI** | 1.41 | -0.32 | 0.92 | -0.04 | -0.25 | | 0.04 | -0.32 | 47.44 |
| | *6.12**** | *-0.87* | *3.75**** | *-0.19* | *-0.82* | | *0.18* | *-1.54* | |
| *Panel B: Decile portfolios based on RtoTR ratio* | | | | | | | | | |
| **CAPM & PI** | 1.32 | -0.12 | 0.66 | | | | | | 19.50 |
| | *5.87**** | *-0.32* | *2.53*** | | | | | | |
| **3FF & PI** | 1.13 | 0.02 | 0.84 | 0.10 | -0.51 | | | | 34.58 |
| | *5.07**** | *0.04* | *3.22**** | *0.45* | *-1.69* | | | | |
| **Carhart & PI** | 1.12 | -0.02 | 0.82 | 0.05 | -0.50 | 0.43 | | | 40.77 |
| | *4.92**** | *-0.05* | *3.25**** | *0.24* | *-1.63* | *0.96* | | | |
| **5FF & PI** | 1.07 | 0.04 | 0.93 | 0.12 | -0.48 | | -0.03 | -0.33 | 45.72 |
| | *4.68**** | *0.11* | *3.71**** | *0.53* | *-1.53* | | *-0.10* | *-1.61* | |

## 3.7 Conclusion

This chapter empirically examines the relationship between stock returns and liquidity using a new price impact ratio as my measure of liquidity. The free-float adjusted price impact ratio established by Karim et al. (2016), which is defined as the absolute daily stock return to the free-float adjusted turnover (RtoTRF ratio) is employed as an alternative to the widely used liquidity measure, the Amihud return to volume ratio (RtoV ratio). Compared to the RtoV ratio, the new liquidity measure is free of size bias. The RtoV ratio suffers from a size bias as small capitalization stocks are less liquid (high RtoV value) than stocks with greater market value. My empirical findings support this argument, because the Spearman rank correlation between RtoV and market value is exceedingly strong ( -0.947), whereas the figure of the RtoTRF ratio is -0.666.

In order to study the impact of the new liquidity measure on asset pricing, I use a data sample of all common stocks listed on three main stock exchanges of US markets from 1997 to 2017. By sorting these stocks into 25 decile portfolios based on the level of free-float price impact ratio, this chapter finds a negative correlation between RtoTRF ratio and expected stock returns. In particular, stocks with low RtoTRF (more liquid shares) have higher post ranking returns, compared to high RtoTRF stocks. This finding is robust when I use alternative asset pricing models. Furthermore, I include a price impact factor (PI) which is defined as the difference in return between portfolios with low RtoTRF and portfolios with high RtoTRF ratios, in order to explain the cross-sectional variation in post-ranking portfolio returns. I find a strong and statistically significant risk premium of PI when using four different asset pricing models including CAPM, three-factor Fama and French model (Fama and French, 1993), four-factor Carhart model (Carhart, 1997), and the five-factor Fama and French model (Fama and French, 2015).

This chapter also tests the efficiency of another alternative to the Amihud ratio, the return to turnover ratio, which is constructed by Florackis, Gregoriou, and Kostakis (2011). Through substituting the denominator of the RtoV with the turnover ratio, they provide evidence that RtoTR is free of size bias when using a sample of listed stocks on the London Stock Exchange in the period from 1991 to 2008. They also suggest that the effect of trading activity dominates trading costs with respect to influencing expected stock returns. In this chapter I report that stocks with low RtoTR (liquid stocks) have higher post-ranking return than high RtoTR stocks, which are in agreement with the results in the UK stock market. The RtoTRF liquidity measure is superior to the RtoTR ratio because it encapsulates the number of shares that are available to the public for trading.

Overall, these findings have important implications for both academics and investors. This chapter tests the accuracy of a new price impact ratio proposed by Karim et al. (2016), which is a more comprehensive alternative to the Amihud ratio as a measure of stock liquidity. As a result, the free float adjusted price impact ratio provides researchers with a more accurate approximation of stock market liquidity, compared to other price impact ratios. This makes a strong contribution to the market microstructure and asset pricing literature. Specifically, the chapter's results should be useful for researchers working in asset pricing, corporate finance, risk management and other research areas, and need a simple but accurate liquidity measure for a long time period. Due to the simplicity in construction, this estimate of liquidity can be applied to many securities in different stock markets, and thus improve the quality of academic research.

From a practical perspective, liquidity is one of the main drivers for the trading frequency of investors. The new superior liquidity measure will improve the efficiency of stock markets, giving investors more confidence in investing. In addition, the positive relationship between the new price impact ratio and stock return indicates that liquidity is significantly related to the trading frequency of investors. As a result, the policy makers should increase the buying and selling volume of stocks in the market as a way to enhance liquidity.

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# CHAPTER 4: ADVERTISING, PRODUCT MARKET COMPETITION, AND STOCK RETURNS

## 4.1 Introduction

Advertising plays a crucial role in increasing differentiation and awareness of a firm in a competitive business environment. It is also important from the perspective of investment as it can improve firms' competitiveness and market performance. There are divided opinions on the role of advertising in financial markets. Jose et al. (1986) suggest some possible benefits of increasing advertising, such as impeding the entry of new firms, differentiating products, declining price elasticity of demand, and increasing shareholder value. As a result, a majority of the empirical research investigates the correlation between advertising expenditures and financial metrics such as sales (Yiannaka, Giannakas, and Tran, 2002; Sridhar, Narayanan, and Srinivasan, 2013), firm's market value (Hirschey and Weygandt,1985; Chauvin and Hirschey, 1993; Graham and Frankenberger, 2000; Sridhar, Narayanan, and Srinivasan, 2013); stock price (Han and Manry, 2004), and stock return (Chan et al., 2001; Eng and Keh, 2007, Vitorino, 2014; Chemmanur and Yan, 2019). A comprehensive review of the literature on the value relevance of advertising expenditure is given by Shah and Akbar (2008).

Previous studies do not account for the effect of competition in the given product market and the influence of advertising on industry concentration and returns. For example, Chan et al. (2001) investigate the relationship between research and development (R&D), advertising expenditures and stock return using the portfolio approach. They find no association between R&D, advertising expenditures, and future stock returns of companies. A recent empirical study on advertising and stock return by Chemmanur and Yan (2019) shows that a higher level of advertising growth is positively correlated to a larger contemporaneous stock return in the advertising year. Meanwhile, a negative relationship is witnessed between advertising growth and stock return in the year subsequent to the advertising year. This result is not driven by product market sales, profitability, and the selection of the advertising sample.

Unlike prior research, this chapter examines the interaction effect of product market competition and advertising on stock returns. It studies the joint impact of product market competition and advertising intensity on stock returns using portfolio sorts, the CAPM by Sharpe (1964) and Lintner (1965), the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama-French (2015) five-factor model technique. Particularly, a conventional double-sorting approach is used to examine the interaction effect between advertising and the competitive degree of industries on expected stock returns. Firms are divided into different groups based on two different breakpoints of the ranked value of advertising intensity, including the New York stock exchange (NYSE) breakpoints and all but micro breakpoints. Details of this approach are discussed in Section 4.3.

Following previous research, this chapter focuses on advertising intensity, expressed as the ratio of advertising expenditures on sales revenue rather than the level of spending on advertising[12]. I find evidence that higher advertising intensity is associated with lower expected stock returns, and this negative relation is stronger for firms in more competitive industries. The tests show that the negative relationship between advertising and stock returns exists only in competitive industries. Indeed, the value-weighted, equal-weighted, and abnormal returns of sorted portfolios decline monotonically with advertising intensity in less concentrated industries. However, this result is not true for firms in more concentrated industries. My findings hold across all asset pricing models, including the CAPM, the Fama-French (1993) three-factor model, the Carhart (1997) four-factor model, and the Fama-French (2015) five-factor model. The results are also robust for both NYSE breakpoints and all but micro breakpoints. For example, using NYSE breakpoint for analyzing, the spreads in equal-weighted

[12] See, for example, Lou (2014) and Vitorino (2014).

and value-weighted returns between low and high advertising intensity in high competitive industries are 0.76% and 0.70%, respectively, and they are statistically significant at the 5% level. Meanwhile, these numbers for concentrated industries are 0.52% and 0.40%, and they are not statistically significant. This result is consistent with Chemmanur and Yan (2019) that a larger advertising growth leads to a smaller stock return in the year subsequent to the advertising year.

This chapter also reports that product market competition is positively correlated to stock returns, and this association exists only among low advertising intensity firms. The portfolio raw returns and abnormal returns increase monotonically with the competitive level in firms with a low ratio of advertising to sales revenue. These results are robust when using different breakpoints and asset pricing models. For instance, when using all but micro breakpoints, the abnormal returns (alpha values) increase with the level of competition in low advertising intensity firms and the high minus low completion alphas are all statistically significant at the 1% level. Further robustness tests are executed on the joint effect of advertising intensity and product market competition on stock returns. The return patterns continue to exist when I use an alternative industry competition measure. Through running subsample tests, this chapter shows that the relation between advertising, competition degree and stock returns are not driven by sample selection.

The chapter has two main contributions to the previous literature. First, it supplements past research studying the correlation between advertising and stock returns (see, e.g., Bublitz and Ettredge, 1989; Eng and Keh, 2007; Chan et al., 2001, and Chemmanur and Yan, 2019). Prior studies show that negative premiums are associated with advertising intensity measures. For instance, Lou (2014) provides evidence that advertising spending leads to a higher abnormal return and then is followed by lower future return. He finds that the low minus high decile ranked by year to year changes in advertising expenditures is 6.96% and 9.84% in the following two years. This return pattern holds after controlling for size, value, momentum, and liquidity factors. This chapter contributes to this literature by showing how the competitive degree of firms in a given industry can affect the association between advertising and stock returns.

Second, this chapter contributes to the association between product market competition and stock returns. Hou and Robinson (2006) empirically demonstrate that firms in more competitive industries earn higher returns even after controlling for size, book to market, and momentum. Meanwhile, Aguerrevere (2009) argues that product market demand can drive the impact of competition on firms' expected returns. He suggests that competitive industries outperform concentrated industries when demand is low, whereas when demand is high firms in more concentrated industries earn higher returns. Recently, Gu (2016) studies the connection between industry competition and returns by considering the effect of firms' R&D intensity. She shows a strong positive interaction effect between R&D investment and product market competition on stock returns. This chapter studies the relationship between competition degree and stock returns under the effect of advertising activities.

The rest of the chapter is organized as follows. Section 4.2 describes my hypothesis development. Section 4.3 documents the data and presents summary statistics. Empirical results and robustness tests are reported in Sections 4.4 and 4.5. Finally, Section 4.6 concludes the chapter.

### 4.2 Hypothesis development

**H1. The negative relationship between advertising and stock return is stronger in competitive industries**.

In this chapter, I provide a more thorough analysis of the correlation between advertising and stock returns under the effect of product market competition. The influence of advertising on financial markets, especially stock returns, attracts significant attention in the academic literature. For example, Chemmanur and Yan (2019) study this relation under the investor attention theory. They examine the relationship between advertising and stock returns in both the short and long run. They show that advertising is positively correlated to stock returns in the advertising year but negatively to stock returns in the subsequent year. They argue that advertising could enhance investor attention, leading to increasing the contemporaneous sales revenue and stock price in the advertising year. However, this attention wears off over time, resulting in stock prices and expected stock returns declining.

Moreover, the causal effect of market structure on advertising is also being considered. The variation in industry structure will alter the incentive of firms to invest in advertising (Chandra and Weinberg, 2018). In addition, Becker and Murphy (1993) predict that firms with market power (high concentration) will undersupply advertising. Hence, I hypothesize that the influence of advertising on stock returns will be stronger for firms in competitive industries.

**H2: Firms in more competitive industries earn higher stock returns than firms in concentrated industries. This relationship is stronger for firms with low advertising intensity.**

In order to examine the interaction effect between advertising intensity and product market competition on stock returns, I empirically test the second hypothesis that there is a positive relationship between the competitive degree of industries and stock returns, and this relation is stronger among low advertising intensity firms.

Prior studies have given potential reasons for the negative effect of product market concentration and stock returns. For instance, Hou and Robinson (2006) explain this relation following a risk-based interpretation, i.e., innovation risk. They argue that firms in more competitive industries are riskier as they engage in more innovation, thus demanding higher expected stock returns. Indeed, they find that the annual returns of firms in the most competitive industries is approximately 4% higher than those in the most concentrated industries. Similarly, Aguerrevere (2009) suggests that firms in competitive industries are riskier when demand is low as a consequence of competition on the value of growth options and from the correlation between the level of demand and the relative riskiness of assets. Recently, Hashem and Su (2015) find that industry concentration is negatively correlated to stock returns in the UK market. In order to explain this result, they suggest that competitive industries have greater distress risks which lead to larger premiums required by investors.

Meanwhile, the relationship between advertising and product market structure has also been studied extensively, see, e.g., Mueller and Rogers (1980), Buxton, Davies, and Lyons (1984), Matraves (1999), and Chandra and Weinberg (2018). Bagwell (2007) argues that in order to enhance monopoly power, firms invest more in advertising to lead through greater concentration. Therefore, it is expected that the positive relation between less concentrated industries and stock returns is stronger for firms with low advertising intensity.

### 4.3 Data and Summary Statistics

#### *4.3.1 Sample selection*

The sample contains all common stocks with share code 10 and 11 in the NYSE/AMEX and NASDAQ stock exchanges. Accounting data such as advertising expenditure, total assets, and sales are collected from COMPUSTAT. Monthly securities data are downloaded from CRSP, over the time period of 1975 to 2018. Only firms with a matching data in both datasets are kept in the sample. I also exclude firm-year observation with missing advertising spending. Following Fama and French (1992), all accounting variables at fiscal year-end in calendar year t-1 are matched with CRSP monthly return data from July of year t to June of year t+1. The minimum six-month gap between fiscal year end and stock return allows the accounting information to be impounded into firm's stock returns. Firms in the financial industry with Standard Industrial Classification (SIC) between 6000 and 6999; and regulated industry with SIC between 4900 and 4999 are excluded from the sample. I also delete observations with negative or zero total assets or sales. Following Lou (2014) and Chemmanur and Yan (2019), only firms with stock prices greater than \$5 are included in the sample. I remove firms with less than 24 month observations. Finally, my sample covers the period from 1977 to 2018.

Advertising intensity is measured by advertising expenditure scaled by sales (AD/sale). This ratio is widely used in previous studies such as Lou (2014) and Vitorino (2014). I use three-digit SIC codes from CRSP in order to classify industries. Following Hou and Robinson (2006) and Chandra and Weiberg (2018), I measure product market competition by the Herfindahl-Hirschman Index (HHI), which is defined as the sum of squared market shares in equation 1:

$$HHI_{jt} = \sum_{i=1}^{N_j} s_{ijt}^2 \tag{4.1}$$

Where $HHI_{jt}$ is the Herfindahl-Hirschman Index of industry *j* in year *t*. $s_{ijt}$ is the market share of firm *i* in industry *j* in year *t*. The market share of each firm is computed as the ratio of firm's sale to total sale value of the entire industry. In order to limit the effect of potential data errors, HHI index is calculated for each industry each year and then average the values over the past three years. HHI index is regularly used by researchers for market structure[13]. A small value of HHI implies that many competing firms share the market, thus the industry is competitive. Meanwhile, a large value of HHI means that the market shares belong to a few large firms, and the industry is concentrated.

In order to investigate the interaction effect between product market competition and advertising on stock returns, I follow Gu (2016) by implementing the double sorting portfolio approach. In particular, in June of each year t, I group all stocks into three portfolios, including the bottom 30% (low), middle 40% (medium), and top 30% (high) based on the ranked value of HHI index in year t-1. Meanwhile, independently, firms with non-missing advertising

[13] See, among others, Hou and Robinson (2006), Giroud and Mueller (2011), Gu (2016), and Chandra and Weiberg (2018).

expenditures are divided into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked value of advertising intensity (ratio advertising/ sale) in calendar year t-1. The interaction of HHI and AD/sale portfolios results in nine portfolios with different characteristics in competition degree and advertising intensity. Following Hou et al. (2014, 2017) and Gu (2016), I apply two different methods to construct breakpoints for advertising intensity. First, firms traded on the NYSE are used to allocate breakpoints for AD/sale, and then these breakpoints are applied to all stocks in the sample. Second, to minimize the effect of microcap firms, I exclude all firms with the market capitalization below the $20^{th}$ NYSE percent. The remaining stocks of the sample are used to calculate breakpoints.

I then compute monthly equal and value-weighted returns on nine portfolios for the period from July of year t to June of year t+1, and rebalance portfolios in June of each year. In order to conduct a thorough comprehensive econometric analysis, I examine the portfolio abnormal performance using four asset pricing models. They are the standard original single factor CAPM, Fama and French three factor model, Carhart four-factor model, and the Fama and French five factor model. According to the single factor CAPM, the expected excess return of a security is a linear function of systematic or market risk.

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \varepsilon_{it} \tag{4.2}$$

Where $R_{it}$ is the return of portfolio i in month t, $R_{ft}$ is risk-free rate return in month t, and $MKT_t$ is the market excess return that is obtained by subtracting the risk free rate from market portfolio return in month t. The next model is the Fama-French three-factor model by Fama and French (1993). It captures the market, value and size factors.

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT} MKT_t + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{it} \tag{4.3}$$

Where $SMB_t$ represents the size factor, $HML_t$ denotes the value risk factor. Other variables are defined as in equation (1). I also estimate the four-factor asset pricing model (Carhart, 1997), by estimating the following equation:

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,MOM}MOM_t + \varepsilon_{it} \quad (4.4)$$

Where $MOM_t$ signifies the past performance factor (momentum). The final model I implement is the Fama and French five-factor model, introduced by Fama and French (2015).

$$R_{it} - R_{ft} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \beta_{i,RMW}RMW_t + \beta_{i,CMA}CMA_t + \varepsilon_{it} \quad (4.5)$$

Where $RMW_t$ and $CMA_t$ stand for profitability and investments, respectively.

*4.3.2 Summary Statistics*

The summary statistics of the sample are reported in Table 4.1. Panel A shows the characteristics of the subsamples of firms in low competitive and high competitive industries. It can be seen that concentrated industries have larger advertising expenditures. The average advertising spending of firms in concentrated industries is \$103.360 million, and it is nearly double the figure of competitive industries. For most variables, low competitive firms have higher mean value than high competitive firms, except for the AD/sale ratio and return. The statistics of non-missing and missing advertising subsamples are presented in Panel B. Firms with advertising spending witness a larger average sales revenue being \$3,075.200 million, whereas this figure for firms with missing advertising expenditure is \$1,983.900 million. Similar patterns are witnessed for other variables such as total assets, market equity, and share price. These results are consistent with Lou (2014).

**Table 4.1: Summary Statistics**

This table reports summary statistics of the sample that covers the period 1977 to 2018. Panel A shows the summary of firms in low competitive industries (top 30% of the rank value Herfindahl-Hirschman index -HHI) and firms in high competitive industries (bottom 30% of the rank value of HHI). Panel B reports summary of firms with missing and non missing advertising expenditure data.

*Panel A: Summary Statistics of low competitive and high competitive firms*

| | Low Competitive (High HHI) | | | | High competitive (Low HHI) | | | |
|---|---|---|---|---|---|---|---|---|
| *Variables* | 25% | Mean | Median | 75% | 25% | Mean | Median | 75% |
| Advertising (million $) | 1.300 | 103.360 | 6.890 | 35.270 | 1.150 | 54.360 | 5.640 | 28.000 |
| Sale (million $) | 117.800 | 4028.700 | 477.200 | 1888.700 | 85.200 | 1786.600 | 297.700 | 1110.500 |
| AD/sale | 0.007 | 0.038 | 0.016 | 0.034 | 0.010 | 0.050 | 0.020 | 0.040 |
| Assets (million $) | 97.300 | 3897.500 | 376.500 | 1691.500 | 85.430 | 2206.380 | 278.240 | 1087.680 |
| Market cap (million $) | 105.600 | 4162.800 | 402.200 | 1779.300 | 106.600 | 3965.500 | 374.100 | 1447.900 |
| Share price ($) | 11.430 | 28.580 | 20.420 | 35.750 | 9.875 | 26.866 | 17.800 | 31.719 |
| Return | -0.050 | 0.019 | 0.010 | 0.072 | -0.056 | 0.020 | 0.010 | 0.084 |

*Panel B: Summary Statistics of non-missing and missing advertising firms*

| | Firms with non-missing advertising expenditure | | | | Firms with missing advertising expenditure | | | |
|---|---|---|---|---|---|---|---|---|
| *Variables* | 25% | Mean | Median | 75% | 25% | Mean | Median | 75% |
| Advertising (million $) | 1.229 | 86.198 | 6.210 | 33.096 | - | - | - | - |
| Sale (million $) | 100.500 | 3075.200 | 380.300 | 1523.200 | 71.700 | 1983.900 | 268.300 | 1042.400 |
| AD/sale | 0.008 | 0.042 | 0.018 | 0.037 | - | - | - | - |
| Assets (million $) | 89.000 | 3399.500 | 321.400 | 1395.000 | 78.100 | 2291.300 | 265.900 | 1063.600 |
| Market cap (million $) | 101.600 | 4520.800 | 383.500 | 1610.300 | 83.500 | 2200.300 | 275.000 | 996.100 |
| Share price | 10.620 | 28.100 | 19.150 | 34.120 | 9.820 | 24.930 | 17.170 | 29.880 |
| Return | -0.052 | 0.019 | 0.010 | 0.078 | -0.058 | 0.023 | 0.009 | 0.086 |

## 4.4 Empirical Results

This section presents the main empirical findings on the interaction effects of advertising intensity and product market competition on expected stock returns.

*4.4.1 Effect of industry competition on advertising-stock return relation*

In order to investigate the influence of industry competition degree on the relationship between advertising intensity and stock return, I apply a double sorting approach. As discussed previously, this procedure results in nine difference portfolio sorts on advertising intensity in combination with HHI index. Table 4.2 reports monthly equal-weighted and value-weighted returns advertising intensity portfolios on low competition and high competition industries, when using two breakpoints for advertising intensity. In Panel A, NYSE breakpoints is used to sort portfolios based on the ranking of advertising intensity. There is a monotonic decrease in portfolio returns with AD/sale in the high competition group. The equal-weighted return declines from 2.11% for the portfolio with low AD/sale to 1.35% for the portfolio with high AD/sale. It leads to a premium of 0.76% for the return on low-minus-high advertising intensity portfolio, and it is statistically significant at the 1% level. Similar positive and significant correlation is witnessed for the spread value-weighted return between low and high advertising intensity portfolios in high competitive industries. Meanwhile, return on the low-minus-high AD/sale portfolios in low competitive industries is negative and insignificant for both equal weighted and value weighted returns. Comparable patterns are seen when all but micro breakpoints are used in Panel B.

The results of asset pricing tests of advertising-return relation in competitive and concentrated industries are presented in Table 4.3 and Table 4.4. Table 4.3 reports the abnormal returns (alpha values) of advertising intensity portfolios with equal-weighted return, whereas the results with value-weighted returns of portfolios are shown in Table 4.4. NYSE breakpoints for advertising intensity are used in Panel A, and I utilize all-but-micro breakpoints in Panel B for both tables.

As displayed in both tables, the abnormal returns on advertising intensity portfolios for firms in high competitive industries declines monotonically with advertising intensity. The alphas on low minus high advertising intensity portfolios are positive and statistically significant for firms in more competitive industries (low HHI), whereas the equivalents for firms in more concentrated industries (high HHI) are negative and insignificant. These results hold for both two breakpoints and different asset pricing models, except for the five factor model alpha in Panel A of Table 4.3. For instance, as shown in Table 4.3 Panel A, the monthly equal weighted CAPM alphas on the low, medium and high advertising intensity portfolios in high competition industries are 0.91%, 0.80% and 0.36%, respectively. The spread between low and high advertising intensity portfolio is 0.55% and significant at the 1% level. Meanwhile, the corresponding values in low competition industries are 0.54%, 0.66%, and 0.66%, respectively. The alpha on the low-minus high advertising intensity portfolios is negative (-0.12%) and insignificant. Table 4.3 Panel B shows the results when using all-but micro breakpoints for advertising intensity portfolios. The alpha values of low minus high advertising intensity portfolio in high competition industries of single factor CAPM, Fama and French three-factor model, Carhart four-factor model and Fama and French five-factor model are 0.63%, 0.68%, 0.75%, and 0.84% respectively. All values are significant at the 1% level.

## Table 4.2: Advertising-return relation in competitive and concentrated industries

This table reports monthly equal weighted return and value weighted return (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the equal weighted and value-weighted portfolio returns. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity, and then report the equal-weighted and value-weighted portfolio returns. The sample period is from July 1977 to December 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low competition (High HHI) | | | | High competition (Low HHI) | | | |
|---|---|---|---|---|---|---|---|---|
| | AD/sale low | AD/sale Medium | AD/sale High | L-H | AD/sale low | AD/sale Medium | AD/sale High | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| EW return | 1.44*** | 1.81*** | 1.96*** | -0.52 | 2.11*** | 1.90*** | 1.35*** | 0.76** |
| | *(5.60)* | *(6.67)* | *(6.85)* | *(-1.36)* | *(7.68)* | *(7.53)* | *(5.55)* | *(2.05)* |
| VW return | 1.24*** | 1.52*** | 1.64*** | -0.40 | 1.98*** | 1.80*** | 1.28*** | 0.70** |
| | *(5.65)* | *(5.75)* | *(6.14)* | *(-1.16)* | *(7.44)* | *(7.51)* | *(6.62)* | *(2.14)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| EW return | 1.44*** | 1.80*** | 1.64*** | -0.20 | 2.16*** | 1.83*** | 1.35*** | 0.81** |
| | *(5.58)* | *(6.88)* | *(6.51)* | *(-0.56)* | *(7.92)* | *(7.56)* | *(6.33)* | *(2.35)* |
| VW return | 1.16*** | 1.79*** | 1.70*** | -0.54 | 1.89*** | 1.78*** | 1.22*** | 0.67** |
| | *(4.95)* | *(7.17)* | *(6.86)* | *(-1.55)* | *(6.84)* | *(7.54)* | *(6.36)* | *(1.99)* |

**Table 4.3: Asset pricing tests with equal weighted returns of portfolios in competitive and concentrated industries**

This table reports abnormal returns of equal - weighted returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the alpha of equal weighted returns of portfolios. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity, and then report the alpha of equal weighted returns of portfolios. The sample period is from July 1977 to December 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low competition (High HHI) | | | | High competition (Low HHI) | | | |
|---|---|---|---|---|---|---|---|---|
| | AD/sale low | AD/sale Medium | AD/sale High | L-H | AD/sale low | AD/sale Medium | AD/sale High | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| CAPM alpha | 0.54*** | 0.66*** | 0.66*** | -0.12 | 0.91*** | 0.80*** | 0.36*** | 0.55*** |
| | *(3.81)* | *(4.69)* | *(4.83)* | *(-0.61)* | *(7.20)* | *(6.68)* | *(3.05)* | *(3.19)* |
| 3FF alpha | 0.41*** | 0.54*** | 0.62*** | -0.2 | 0.89*** | 0.72*** | 0.30*** | 0.59*** |
| | *(3.26)* | *(4.42)* | *(4.98)* | *(-1.14)* | *(10.25)* | *(7.86)* | *(3.04)* | *(4.48)* |
| Carhart alpha | 0.50*** | 0.59*** | 0.66*** | -0.16 | 0.95*** | 0.80*** | 0.40*** | 0.55*** |
| | *(3.97)* | *(4.79)* | *(5.25)* | *(-0.90)* | *(10.89)* | *(8.83)* | *(4.03)* | *(4.18)* |
| 5FF alpha | 0.26** | 0.42*** | 0.65*** | -0.39** | 0.85*** | 0.56*** | 0.21** | 0.64*** |
| | *(2.09)* | *(3.38)* | *(5.08)* | *(-2.17)* | *(9.53)* | *(6.21)* | *(2.01)* | *(4.71)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| CAPM alpha | 0.51*** | 0.71*** | 0.59*** | -0.08 | 1.00*** | 0.77*** | 0.37*** | 0.63*** |
| | *(3.31)* | *(5.20)* | *(4.27)* | *(-0.39)* | *(8.13)* | *(6.76)* | *(3.73)* | *(3.99)* |
| 3FF alpha | 0.45*** | 0.63*** | 0.55*** | -0.10 | 1.02*** | 0.72*** | 0.34*** | 0.68*** |
| | *(3.04)* | *(4.97)* | *(4.31)* | *(-0.51)* | *(9.58)* | *(6.98)* | *(3.54)* | *(4.72)* |
| Carhart alpha | 0.48*** | 0.71*** | 0.62*** | -0.14 | 1.12*** | 0.83*** | 0.37*** | 0.75*** |
| | *(3.23)* | *(5.61)* | *(4.79)* | *(-0.71)* | *(10.66)* | *(8.06)* | *(3.81)* | *(5.19)* |
| 5FF alpha | 0.21 | 0.50*** | 0.53*** | -0.32 | 1.00*** | 0.56*** | 0.16* | 0.84*** |
| | *(1.45)* | *(3.91)* | *(3.99)* | *(-1.63)* | *(9.09)* | *(5.48)* | *(1.71)* | *(5.74)* |

**Table 4.4: Asset pricing test with value weighted returns of portfolios in competitive and concentrated industries**

This table reports abnormal returns of value- weighted returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the alpha of value- weighted returns of portfolios. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity, and then report the alpha of value- weighted returns of portfolios. The sample period is from July 1977 to December 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low competition (High HHI) | | | | High competition (Low HHI) | | | |
|---|---|---|---|---|---|---|---|---|
| | AD/sale low | AD/sale Medium | AD/sale High | L-H | AD/sale low | AD/sale Medium | AD/sale High | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| CAPM alpha | 0.41** | 0.48*** | 0.61*** | -0.2 | 0.88*** | 0.75*** | 0.40*** | 0.48*** |
| | *(2.43)* | *(2.90)* | *(3.53)* | *(-0.83)* | *(6.21)* | *(6.71)* | *(3.55)* | *(2.65)* |
| 3FF alpha | 0.34** | 0.45*** | 0.56*** | -0.22 | 0.94*** | 0.83*** | 0.44*** | 0.50*** |
| | *(2.04)* | *(2.66)* | *(3.24)* | *(-0.91)* | *(6.83)* | *(7.72)* | *(3.99)* | *(2.84)s* |
| Carhart alpha | 0.47** | 0.59*** | 0.60*** | -0.13 | 0.93*** | 0.89*** | 0.40*** | 0.53*** |
| | *(2.82)* | *(3.53)* | *(3.40)* | *(-0.53)* | *(6.65)* | *(8.13)* | *(3.57)* | *(2.96)* |
| 5FF alpha | 0.22 | 0.34** | 0.39** | -0.17 | 0.91*** | 0.83*** | 0.22** | 0.69*** |
| | *(1.25)* | *(1.98)* | *(2.20)* | *(-0.69)* | *(6.35)* | *(7.44)* | *(2.01)* | *(3.85)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| CAPM alpha | 0.33* | 0.79*** | 0.60*** | -0.27 | 0.77*** | 0.74*** | 0.35*** | 0.42** |
| | *(1.83)* | *(5.01)* | *(3.77)* | *(-1.11)* | *(5.12)* | *(6.75)* | *(3.09)* | *(2.22)* |
| 3FF alpha | 0.31* | 0.76*** | 0.61*** | -0.30 | 0.85*** | 0.82*** | 0.40*** | 0.45** |
| | *(1.69)* | *(4.75)* | *(3.80)* | *(-1.23)* | *(5.71)* | *(7.78)* | *(3.79)* | *(2.46)* |
| Carhart alpha | 0.25 | 0.75*** | 0.61*** | -0.36 | 0.88*** | 0.90*** | 0.41*** | 0.47** |
| | *(1.33)* | *(4.60)* | *(3.71)* | *(-1.45)* | *(5.79)* | *(8.45)* | *(3.75)* | *(2.52)* |
| 5FF alpha | 0.05 | 0.51*** | 0.45*** | -0.40 | 0.83*** | 0.84*** | 0.21** | 0.62*** |
| | *(0.28)* | *(3.19)* | *(2.73)* | *(-1.62)* | *(5.39)* | *(7.59)* | *(2.01)* | *(3.32)* |

Table 4.4 shows similar findings concerning the abnormal return of advertising intensity portfolios in low and high competition industries. The value-weighted CAPM alpha value of low, medium and high advertising/sale portfolio in high competition industries, when using NYSE breakpoints are 0.88%, 0.75%, and 0.40% with statistical significance at 1% level. The spread of low minus high advertising intensity portfolio is 0.48% and statistically significant at the 1% level. The highest spread is seen in the five-factor model (0.69%). In contrast, the single factor CAPM alpha value on low minus high advertising intensity portfolio is negative at -0.20% and insignificant for low competition industries. Similar return patterns are seen in Panel B when using all but micro breakpoints, but with smaller returns' magnitude.

In summary, the empirical findings in this section provide evidence that portfolios with high advertising intensity have lower average return, and abnormal return- alpha value, compared to a low advertising intensity portfolio. The return difference between low and high advertising intensity portfolio is positive and statistically significant for firms in high competition group only. Being consistent with the first hypothesis, these results suggests that there is a negative relationship between advertising and stock return, and this correlation is stronger in a more competitive industry. This finding holds after using two different breakpoint methods for advertising intensity and reporting both equal-weight and value-weight returns of the portfolio. Previous papers in the literature also support for this discovery. For example, Chemmanur and Yan (2018) indicate that an increase in advertising could lead to a decrease in stock return in the long run subsequent to the advertising year. Furthermore, my findings also suggest that abnormal returns of advertising intensity portfolios become negative for firms in high concentrated industries. The effect of advertising on firms' returns can be significantly different for two firms with the same advertising intensity, who operate in two industries with different market structure.

*4.4.2 Effect of advertising intensity on industry competition-return relation*

This subsection presents results of the second hypothesis, which states that the positive association between industry competition and stock returns is stronger among low advertising intensity firms. Table 4.5 displays monthly equal-weighted and value-weighted returns of competition portfolios among low advertising intensity (bottom 30% of the advertising distribution) and high advertising intensity firms (top 30% of the advertising distribution). Panel A shows the results when using NYSE breakpoints for advertising intensity, and the results of all but micro breakpoints are shown in Panel B. Industry with a low HHI means that it is a competitive industry while a high HHI suggests that the industry is more concentrated. First, when NYSE breakpoints are used for analysis, the monthly equal-weighted returns of high, medium, and low HHI index in advertising-weak group are 1.44%, 2.10% and 2.11%, respectively. The return on low minus high HHI portfolio is positive at 0.67% and statistically significant at the 5% level. The monthly value-weighted return shows a familiar pattern but with a higher magnitude for the low advertising intensity group. Meanwhile, the spread of low minus high HHI portfolio's returns become negative and insignificant for companies in the advertising-intensive group. These findings remain intact when using all but micro breakpoints for advertising intensity as shown in Table 4.5 Panel B.

**Table 4.5: Competition-return among high and low advertising intensity firms**

This table reports monthly equal weighted return and value weighted return (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the equal weighted and value-weighted portfolio returns. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity, and then report the equal-weighted and value-weighted portfolio returns. The sample period is from July 1977 to December 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low AD/sale | | | | High AD/sale | | | |
|---|---|---|---|---|---|---|---|---|
| | HHI High | HHI Medium | HHI Low | L-H | HHI High | HHI Medium | HHI Low | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| EW return | 1.44*** | 2.10*** | 2.11*** | 0.67** | 1.96*** | 1.85*** | 1.36*** | -0.60 |
| | *(5.60)* | *(7.68)* | *(7.68)* | *(2.36)* | *(6.85)* | *(6.45)* | *(5.56)* | *(-1.59)* |
| VW return | 1.24*** | 1.57*** | 1.98*** | 0.74** | 1.64*** | 1.46*** | 1.28*** | -0.36 |
| | *(5.65)* | *(5.89)* | *(7.44)* | *(2.14)* | *(6.14)* | *(6.28)* | *(6.62)* | *(-1.10)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| EW return | 1.44*** | 1.72*** | 2.15*** | 0.71* | 1.64*** | 1.52*** | 1.35*** | -0.29 |
| | *(5.58)* | *(6.86)* | *(7.79)* | *(1.91)* | *(6.51)* | *(6.07)* | *(6.33)* | *(-0.90)* |
| VW return | 1.17*** | 1.64*** | 1.89*** | 0.72** | 1.70*** | 1.36*** | 1.22*** | -0.48 |
| | *(4.95)* | *(6.8)* | *(6.84)* | *(1.99)* | *-6.86* | *(6.05)* | *(6.36)* | *(-1.53)* |

Tables 4.6 and 4.7 display the abnormal returns on competition portfolios of two groups including advertising-intensive and advertising-weak firms. Table 6 presents the results of asset pricing tests with equal-weighted portfolio returns. As illustrated in both panels, for the low advertising intensity group, firms in competitive industries outperform concentrated industries by earning higher abnormal returns over the sample period. The low minus high HHI portfolio's return is positive and statistically significant. These results are robust for all four asset pricing models and two different breakpoints for advertising intensity. For instance, the equal-weighted five-factor model alpha values of high, medium and low HHI portfolios for the advertising-weak group are 0.26%, 0.59%, 0.85%, respectively, and are all significant at the 5% level. The spread between low and high HHI portfolios' alpha is as large as 0.59% and significant at the 1% level. The corresponding values in the high advertising intensity group are 0.65%, 0.58%, and 0.21% with a significance level at the 1% and 5% level in all cases. Interestingly, the three-factor and five-factor model alphas of low minus high HHI portfolios are negative at -0.32% and -0.44%, and significant at the 5% level. Moreover, the single factor CAPM alpha, three-factor model alpha, and four-factor model alpha for low minus high HHI portfolios of advertising-weak group are 0.37%, 0.48%, and 0.45%, with 5% significance level. In contrast, the corresponding values for the advertising intensive group become negative at -0.29%, -0.32%, respectively, and are statistically insignificant.

Panel B reports a comparable pattern but with stronger results. For instance, the equal-weighted five-factor model alphas of high, medium, low HHI portfolios for low advertising/sale group are 0.21%, 0.60%, and 1.01%, respectively. The spread alpha is positive at 0.80% and statistically significant at the 1% level. The estimates of CAPM, three-factor model and four-factor model alphas are 0.49%, 0.57%, and 0.65% respectively, and statistically significant at the 1% level. The abnormal returns of competition portfolios in high advertising intensity group are negative and insignificant in all cases except for the five factor model.

**Table 4.6: Asset pricing test with equal weighted returns of portfolios among high and low advertising intensity firms**

This table reports abnormal returns of equal - weighted returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the alpha of equal weighted returns of portfolios. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity, and then report the alpha of equal weighted returns of portfolios. The sample period is from July 1977 to December 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low AD/sale | | | | High AD/sale | | | |
|---|---|---|---|---|---|---|---|---|
| | HHI High | HHI Medium | HHI Low | L-H | HHI High | HHI Medium | HHI Low | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| CAPM alpha | 0.54*** | 0.56*** | 0.91*** | 0.37** | 0.65*** | 0.56*** | 0.36*** | -0.29 |
| | *(3.81)* | *(4.39)* | *(7.20)* | *(1.96)* | *(4.83)* | *(4.26)* | *(3.05)* | *(-1.62)* |
| 3FF alpha | 0.41*** | 0.51*** | 0.89*** | 0.48*** | 0.62*** | 0.54*** | 0.30*** | -0.32** |
| | *(3.26)* | *(5.66)* | *(10.25)* | *(3.17)* | *(4.98)* | *(5.22)* | *(3.04)* | *(-2.01)* |
| Carhart alpha | 0.50*** | 0.61*** | 0.95*** | 0.45*** | 0.66*** | 0.62*** | 0.40*** | -0.26 |
| | *(3.97)* | *(6.99)* | *(10.89)* | *(2.96)* | *(5.25)* | *(6.04)* | *(4.03)* | *(-1.62)* |
| 5FF alpha | 0.26** | 0.59*** | 0.85*** | 0.59*** | 0.65*** | 0.58*** | 0.21** | -0.44*** |
| | *(2.09)* | *(6.38)* | *(9.53)* | *(3.83)* | *(5.08)* | *(5.48)* | *(2.01)* | *(-2.69)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| CAPM alpha | 0.51*** | 0.64*** | 1.00*** | 0.49*** | 0.59*** | 0.45*** | 0.37*** | -0.22 |
| | *(3.31)* | *(5.41)* | *(8.13)* | *(2.47)* | *(4.27)* | *(3.57)* | *(3.73)* | *(-1.30)* |
| 3FF alpha | 0.45*** | 0.61*** | 1.02*** | 0.57*** | 0.55*** | 0.45*** | 0.34*** | -0.21 |
| | *(3.04)* | *(6.17)* | *(9.58)* | *(3.14)* | *(4.31)* | *(3.88)* | *(3.54)* | *(-1.31)* |
| Carhart alpha | 0.48*** | 0.72*** | 1.13*** | 0.65*** | 0.62*** | 0.60*** | 0.37*** | -0.25 |
| | *(3.23)* | *(7.51)* | *(10.66)* | *(3.55)* | *(4.79)* | *(5.31)* | *(3.81)* | *(-1.54)* |
| 5FF alpha | 0.21 | 0.60*** | 1.01*** | 0.80*** | 0.53*** | 0.51*** | 0.16* | -0.37** |
| | *(1.45)* | *(5.93)* | *(9.09)* | *(4.39)* | *(3.99)* | *(4.31)* | *(1.71)* | *(-2.27)* |

Table 4.7 repeats the same analysis with value weighted returns of portfolios among high and low advertising intensity firms. As illustrated in Panel A, the abnormal returns of portfolios in advertising-weak group increase monotonically with the degree of product market competition, whereas the opposite trend is seen for firms in the advertising –intensive group. For instance, the three-factor model alpha values of high, medium, and low HHI portfolios of low advertising intensity group are 0.34%, 0.61%, and 0.94%, respectively, and significant at a minimum of 5% for all cases. The alpha of low minus high HHI portfolio is 0.60% and statistically significant at the 1% level. The five-factor model raises the highest low minus high abnormal return at 0.69%, while the lowest value belongs to the CAPM alpha. The corresponding figures of high advertising intensity group are 0.56%, 0.64%, 0.43%, respectively. The low minus high spread is -0.13% and insignificant. Panel B shows similar return patterns when using all but micro breakpoints for advertising intensity portfolios.

Overall, the results of raw and abnormal returns displayed in Tables 4.5, 4.6 and 4.7 overwhelmingly support the second hypothesis that there is a positive relationship between industry competition and stock return. In particular, firms in competitive industries gain higher average return than firms in concentrated industries, and this difference is statistically significant at the 5% and 10% levels. Similar findings are seen when using asset pricing tests for abnormal returns of portfolios with different competition levels in two groups including low and high advertising intensity. These results are consistent with the findings of Hou and Robinson (2006), Hashem and Su (2015), and Gu (2016). For instance, Hou and Robinson (2006) suggest that firms in more concentrated industries earn lower returns, even after controlling for some factors such as size and book-to-market ratio.

**Table 4.7: Asset pricing test with value weighted returns of portfolios among high and low advertising intensity firms**

This table reports abnormal returns of value- weighted returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the alpha of value- weighted returns of portfolios. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity, and then report the alpha of value- weighted returns of portfolios. The sample period is from July 1977 to December 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low AD/sale | | | | High AD/sale | | | |
|---|---|---|---|---|---|---|---|---|
| | HHI High | HHI Medium | HHI Low | L-H | HHI High | HHI Medium | HHI Low | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| CAPM alpha | 0.41** | 0.54*** | 0.88*** | 0.47** | 0.61*** | 0.53*** | 0.40*** | -0.21 |
| | *(2.43)* | *(3.14)* | *(6.21)* | *(2.13)* | *(3.53)* | *(3.42)* | *(3.55)* | *(-1.02)* |
| 3FF alpha | 0.34** | 0.61*** | 0.94*** | 0.60*** | 0.56*** | 0.64*** | 0.43*** | -0.13 |
| | *(2.04)* | *(3.59)* | *(6.83)* | *(2.76)* | *(3.24)* | *(4.29)* | *(3.99)* | *(-0.73)* |
| Carhart alpha | 0.47*** | 0.67*** | 0.93*** | 0.46** | 0.60*** | 0.69*** | 0.40*** | -0.20 |
| | *(2.82)* | *(3.88)* | *(6.65)* | *(2.10)* | *(3.40)* | *(4.54)* | *(3.57)* | *(-0.96)* |
| 5FF alpha | 0.22 | 0.66*** | 0.91*** | 0.69*** | 0.39** | 0.59*** | 0.22** | -0.17 |
| | *(1.25)* | *(3.78)* | *(6.35)* | *(3.09)* | *(2.20)* | *(3.79)* | *(2.01)* | *(-0.82)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| CAPM alpha | 0.33* | 0.67*** | 0.77*** | 0.44* | 0.60*** | 0.43*** | 0.35*** | -0.25 |
| | *(1.83)* | *(4.32)* | *(5.12)* | *(1.85)* | *(3.77)* | *(3.00)* | *(3.09)* | *(-1.28)* |
| 3FF alpha | 0.31* | 0.72*** | 0.85*** | 0.54** | 0.61*** | 0.55*** | 0.40*** | -0.21 |
| | *(1.69)* | *(4.61)* | *(5.71)* | *(2.28)* | *(3.80)* | *(4.02)* | *(3.79)* | *(-1.09)* |
| Carhart alpha | 0.25 | 0.73*** | 0.88*** | 0.63*** | 0.61*** | 0.62*** | 0.41*** | -0.20 |
| | *(1.33)* | *(4.58)* | *(5.79)* | *(2.62)* | *(3.71)* | *(4.48)* | *(3.75)* | *(-1.02)* |
| 5FF alpha | 0.05 | 0.72*** | 0.83*** | 0.78*** | 0.45*** | 0.53*** | 0.22** | -0.23 |
| | *(0.28)* | *(4.45)* | *(5.39)* | *(3.24)* | *(2.73)* | *(3.76)* | *(2.01)* | *(-1.18)* |

## 4.5 Robustness

### *4.5.1 Subsample tests*

As a robustness check, the whole sample is divided into two sub-periods, which are 1977-1993 and 1996-2018 periods because of a regulatory change in reporting advertising costs in 1994. Statement of Position (SOP) 93-7- Reporting on Advertising Costs was issued on June 1994 by the Accounting Standards Executive Committee (Lou, 2014). Tables 4.8 and 4.9 presents the robust results of the advertising-return and competition-return relation for subsamples, respectively. For both tables, I use NYSE breakpoints for advertising intensity and report the monthly value-weighted portfolio returns.

The monthly returns and alpha value patterns in the two subsamples are similar to the full sample reported in Tables 4.4 and 4.7, in terms of economic magnitude and statistical significance. For instance, the results of the period from 1977 to 1993 are reported in Panel A, Table 8. The four-factor model alphas on low, medium and high advertising intensity for low competition industries are 0.51%, 0.77%, 0.75% respectively, and significant at the 5% level. The low minus high abnormal return is –0.24% and insignificant. Meanwhile, the corresponding numbers for high competition group are 1.22%, 0.80%, 0.40% respectively, and statistically significant at the 5% level. The spread of the low advertising intensity and the high advertising intensity portfolios is positive and significant at the 1% level. Interestingly, the period from 1996 to 2018 experiences a stronger result with respect to significance levels, compared with the period between 1977-1993. Similarly, when considering the competition-return relation, Table 4.9 presents results consistent with the whole sample outcomes in Table 4.7. The empirical analysis shows that hypothesis 2 is robust across all subsamples.

**Table 4.8: Advertising - return relation and subsample studies**

This table reports monthly value weighted return and abnormal returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity using NYSE breakpoints for advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, the subsample covers the period from 1977 to 1993. In Panel B, the sample period is from 1996 to 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low competition (High HHI) | | | | High competition (Low HHI) | | | |
|---|---|---|---|---|---|---|---|---|
| | AD/sale low | AD/sale Medium | AD/sale High | L-H | AD/sale low | AD/sale Medium | AD/sale High | L-H |
| ***Panel A: The period from 1977 to 1993*** | | | | | | | | |
| VW return | 1.36*** | 1.87*** | 2.12*** | -0.76 | 2.36*** | 2.03*** | 1.33*** | 1.03* |
| | *(3.71)* | *(4.44)* | *(4.63)* | *(-1.31)* | *(5.52)* | *(5.14)* | *(4.25)* | *(1.95)* |
| CAPM alpha | 0.23 | 0.52** | 0.64*** | -0.41 | 0.85*** | 0.66*** | 0.30* | 0.55* |
| | *(1.10)* | *(2.33)* | *(2.74)* | *(-1.29)* | *(3.31)* | *(4.72)* | *(1.85)* | *(1.81)* |
| 3FF alpha | 0.37* | 0.58** | 0.70*** | -0.33 | 1.06*** | 0.66*** | 0.40** | 0.67** |
| | *(1.69)* | *(2.54)* | *(2.90)* | *(-1.02)* | *(4.09)* | *(4.66)* | *(2.51)* | *(2.20)* |
| Carhart alpha | 0.51** | 0.77*** | 0.75*** | -0.24 | 1.22*** | 0.80*** | 0.40** | 0.82*** |
| | *(2.29)* | *(3.32)* | *(3.01)* | *(-0.72)* | *(4.59)* | *(5.62)* | *(2.35)* | *(2.61)* |
| 5FF alpha | 0.45* | 0.85*** | 0.57** | -0.12 | 1.15*** | 0.66*** | 0.23 | 0.92*** |
| | *(1.89)* | *(3.39)* | *(2.13)* | *(-0.33)* | *(4.02)* | *(4.21)* | *(1.32)* | *(2.73)* |
| ***Panel B: The period from 1996 to 2018*** | | | | | | | | |
| VW return | 0.98*** | 1.22*** | 1.19*** | -0.21 | 2.01*** | 1.65*** | 1.08*** | 0.93** |
| | *(3.06)* | *(3.41)* | *(3.37)* | *(-0.62)* | *(5.52)* | *(5.09)* | *(4.21)* | *(2.08)* |
| CAPM alpha | 0.28 | 0.45* | 0.43* | -0.15 | 1.18*** | 0.85*** | 0.45*** | 0.73*** |
| | *(1.26)* | *(1.82)* | *(1.76)* | *(-0.45)* | *(5.24)* | *(4.94)* | *(2.76)* | *(2.62)* |
| 3FF alpha | 0.19 | 0.40 | 0.39 | -0.20 | 1.20*** | 0.93*** | 0.46*** | 0.74*** |
| | *(0.89)* | *(1.64)* | *(1.61)* | *(-0.62)* | *(5.48)* | *(5.72)* | *(2.98)* | *(2.75)* |
| Carhart alpha | 0.27 | 0.53** | 0.45* | -0.18 | 1.18*** | 0.97*** | 0.42*** | 0.76*** |
| | *(1.28)* | *(2.21)* | *(1.85)* | *(-0.55)* | *(5.33)* | *(5.93)* | *(2.70)* | *(2.80)* |
| 5FF alpha | -0.03 | 0.25 | 0.43* | -0.46 | 1.16*** | 0.91*** | 0.20 | 0.96*** |
| | *(-0.16)* | *(0.99)* | *-1.71* | *(1.38)* | *(5.05)* | *(5.39)* | *(1.34)* | *(3.49)* |

**Table 4.9: Competition-return relation and subsample studies**

This table reports monthly equal weighted return, value weighted return and abnormal returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity using NYSE breakpoints for advertising intensity. Product market competition is measured by Herfindahl-Hirschman index (HHI). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, the subsample covers the period from 1977 to 1993. In Panel B, the sample period is from 1996 to 2018. t-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low AD/sale | | | | High AD/sale | | | |
|---|---|---|---|---|---|---|---|---|
| | HHI High | HHI Medium | HHI Low | L-H | HHI High | HHI Medium | HHI Low | L-H |
| ***Panel A: The period from 1977 to 1993*** | | | | | | | | |
| VW return | 1.36*** | 1.41*** | 2.36*** | 1.00* | 2.12*** | 1.73*** | 1.33*** | -0.79 |
| | *(3.71)* | *(3.61)* | *(5.52)* | *(1.78)* | *(4.63)* | *(4.45)* | *(4.25)* | *(-1.43)* |
| CAPM alpha | 0.23 | 0.07 | 0.85*** | 0.62* | 0.64*** | 0.48** | 0.30* | -0.34 |
| | *(1.10)* | *(0.42)* | *(3.31)* | *(1.86)* | *(2.74)* | *(2.02)* | *(1.85)* | *(-1.20)* |
| 3FF alpha | 0.37* | 0.10 | 1.06*** | 0.69** | 0.70*** | 0.66*** | 0.40** | -0.30 |
| | *(1.69)* | *(0.59)* | *(4.09)* | *(2.05)* | *(2.90)* | *(2.73)* | *(2.51)* | *(-1.04)* |
| Carhart alpha | 0.51** | 0.18 | 1.22*** | 0.71** | 0.75*** | 0.69*** | 0.40** | -0.35 |
| | *(2.29)* | *(0.99)* | *(4.59)* | *(2.05)* | *(3.01)* | *(2.74)* | *(2.35)* | *(-1.17)* |
| 5FF alpha | 0.45* | 0.13 | 1.15*** | 0.70* | 0.57** | 0.36 | 0.23 | -0.34 |
| | *(1.89)* | *(0.66)* | *(4.02)* | *(1.87)* | *(2.13)* | *(1.38)* | *(1.32)* | *(-1.06)* |
| ***Panel B: The period from 1996 to 2018*** | | | | | | | | |
| VW return | 0.98*** | 1.64*** | 2.01*** | 1.03** | 1.19*** | 1.18*** | 1.08*** | -0.11 |
| | *(3.06)* | *(4.25)* | *(5.52)* | *(2.12)* | *(3.37)* | *(3.85)* | *(4.21)* | *(-0.26)* |
| CAPM alpha | 0.29 | 0.86*** | 1.18*** | 0.89*** | 0.43* | 0.50** | 0.45*** | 0.02 |
| | *(1.26)* | *(3.08)* | *(5.24)* | *(2.78)* | *(1.76)* | *(2.35)* | *(2.76)* | *(0.07)* |
| 3FF alpha | 0.19 | 0.91*** | 1.20*** | 1.01*** | 0.39 | 0.58*** | 0.46*** | 0.07 |
| | *(0.89)* | *(3.29)* | *(5.48)* | *(3.30)* | *(1.61)* | *(2.81)* | *(2.98)* | *(0.24)* |
| Carhart alpha | 0.27 | 0.96*** | 1.18*** | 0.91*** | 0.45* | 0.64*** | 0.42*** | -0.03 |
| | *(1.28)* | *(3.46)* | *(5.33)* | *(2.96)* | *(1.85)* | *(3.11)* | *(2.70)* | *(-0.10)* |
| 5FF alpha | -0.03 | 1.00*** | 1.16*** | 1.19*** | 0.43* | 0.60*** | 0.20 | -0.23 |
| | *(-0.16)* | *(3.49)* | *(5.05)* | *(3.78)* | *(1.71)* | *(2.78)* | *(1.34)* | *(-0.78)* |

*4.5.2 Alternative HHI index*

In this subsection, I use an alternative index to measure market share concentration as a robustness check. According to Hay and Morris (1991), and Ali et al. (2009), the HHI index only considers public firms listed on a U.S stock exchange, which leads to a problem of missing private companies in calculating industry concentration. As a result, Hoberg and Phillips (2010) construct an alternative Herfindahl Index using both private and public companies. The results of using this alternative concentration measure are displayed in Tables 4.10 and 4.11. For both tables, Panel A shows the results using NYSE breakpoints with equal-weighted portfolio returns, and Panel B reports the value-weighted portfolio returns with all but micro breakpoints. Tables 4.10 and 4.11 report the results of the advertising-return and competition-return associations, respectively using the alternative product market competition measure, which is introduced by Hoberg and Phillips (2010).

The empirical estimates from Tables 4.10 and 4.11 are comparable to the results when I use the HHI index of Hou and Robinson (2006). This implies that the findings of this chapter are not driven by product market competition measure.

**Table 4.10: Advertising-return relation with alternative product market competition measure**

This table reports monthly equal weighted return, value weighted return and abnormal returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by alternative Herfindahl-Hirschman index (HHI) in Hoberg and Phillips (2010). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the alpha of value- weighted returns of portfolios. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity. T-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low competitive (High HHI) | | | | High competitive (Low HHI) | | | |
|---|---|---|---|---|---|---|---|---|
| | AD/sale low | AD/sale Medium | AD/sale High | L-H | AD/sale low | AD/sale Medium | AD/sale High | L-H |
| ***Panel A: NYSE breakpoints and equal weighted return*** | | | | | | | | |
| EW return | 1.23*** | 1.73*** | 1.86*** | -0.63 | 2.24*** | 2.16*** | 1.20*** | 1.04** |
| | *(3.99)* | *(5.38)* | *(5.74)* | *(-1.38)* | *(5.98)* | *(6.56)* | *(3.63)* | *(2.08)* |
| CAPM alpha | 0.28 | 0.55*** | 0.75*** | -0.47 | 0.92*** | 0.93*** | 0.28 | 0.64** |
| | *(1.32)* | *(2.90)* | *(3.30)* | *(-1.52)* | *(4.53)* | *(5.33)* | *(1.31)* | *(2.19)* |
| 3FF alpha | 0.11 | 0.15 | 0.49** | -0.38 | 0.91*** | 0.81*** | 0.29 | 0.62*** |
| | *(0.54)* | *(0.92)* | *(2.29)* | *(-1.29)* | *(6.87)* | *(6.79)* | *(1.58)* | *(2.70)* |
| Carhart alpha | 0.23 | 0.31* | 0.62*** | -0.39 | 1.14*** | 1.03*** | 0.52*** | 0.62*** |
| | *(1.13)* | *(1.93)* | *(2.85)* | *(-1.31)* | *(9.08)* | *(9.26)* | *(2.86)* | *(2.79)* |
| 5FF alpha | -0.02 | -0.11 | 0.34 | -0.36 | 1.03*** | 0.86*** | 0.50*** | 0.53** |
| | *(-0.10)* | *(-0.71)* | *(1.59)* | *(1.21)* | *(7.68)* | *(6.99)* | *(2.64)* | *(2.29)* |
| ***Panel B: All but micro breakpoints and value weighted return*** | | | | | | | | |
| VW return | 1.11*** | 1.70*** | 1.84*** | -0.73 | 2.12*** | 2.05*** | 1.15*** | 0.97** |
| | *(3.95)* | *(5.33)* | *(5.35)* | *(-1.64)* | *(5.54)* | *(6.68)* | *(4.55)* | *(2.12)* |
| CAPM alpha | 0.34* | 0.53*** | 0.84*** | -0.50 | 0.79*** | 0.87*** | 0.30** | 0.49* |
| | *(1.67)* | *(2.79)* | *(2.92)* | *(-1.45)* | *(3.68)* | *(5.43)* | *(2.17)* | *(1.90)* |
| 3FF alpha | 0.20 | 0.19 | 0.65** | -0.45 | 1.01*** | 1.02*** | 0.42*** | 0.59** |
| | *(0.99)* | *(1.04)* | *(2.27)* | *(-1.28)* | *(4.74)* | *(6.36)* | *(2.98)* | *(2.32)* |
| Carhart alpha | 0.23 | 0.35* | 0.69** | -0.46 | 1.14*** | 1.21*** | 0.44*** | 0.70*** |
| | *(1.09)* | *(1.95)* | *(2.34)* | *(-1.27)* | *(5.28)* | *(7.62)* | *(3.09)* | *(2.70)* |
| 5FF alpha | 0.03 | 0.07 | 0.18 | -0.15 | 1.15*** | 1.10*** | 0.28** | 0.87*** |
| | *(0.17)* | *(0.36)* | *(0.67)* | *(-0.44)* | *(5.28)* | *(6.65)* | *(1.97)* | *(3.35)* |

**Table 4.11: Competition-return relation with alternative product market competition measure**

This table reports monthly equal weighted return, value weighted return and abnormal returns (in percent) of portfolios sorted on product market competition (HHI) and advertising intensity. Product market competition is measured by alternative Herfindahl-Hirschman index (HHI) in Hoberg and Phillips (2010). Advertising intensity is defined as advertising expenditure scaled by sale (AD/sale). In June of each year t, NYSE, Amex, and Nasdaq stocks are divided into three groups using the breakpoints for the bottom 30% (low), middle 40% (medium), and top 30% (high) of the ranked values of HHI in year t-1. Independently, firms with non-missing advertising are grouped into three portfolios based on the breakpoints for the bottom 30%, middle 40%, and top 30% of the ranked values of AD/sale in year t-1. In Panel A, I use NYSE breakpoints for advertising intensity and report the alpha of value- weighted returns of portfolios. In Panel B, I exclude stocks with market equity below the 20th NYSE percentile, use the remaining stocks to calculate breakpoints for advertising intensity. T-statistics are reported in parentheses. The significance levels 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

| | Low AD/sale | | | | High AD/sale | | | |
|---|---|---|---|---|---|---|---|---|
| | HHI High | HHI Medium | HHI Low | L-H | HHI High | HHI Medium | HHI Low | L-H |
| ***Panel A: NYSE breakpoints*** | | | | | | | | |
| EW return | 1.23*** | 1.90*** | 2.24*** | 1.01** | 1.86*** | 1.58*** | 1.20*** | -0.66 |
| | *(3.99)* | *(6.02)* | *(5.98)* | *(2.06)* | *(5.74)* | *(6.02)* | *(3.63)* | *(-1.43)* |
| CAPM alpha | 0.28 | 0.70*** | 0.92*** | 0.64** | 0.75*** | 0.51*** | 0.28 | -0.47 |
| | *(1.32)* | *(4.18)* | *(4.53)* | *(2.20)* | *(3.30)* | *(3.53)* | *(1.31)* | *(-1.51)* |
| 3FF alpha | 0.11 | 0.37** | 0.91*** | 0.80*** | 0.49** | 0.34** | 0.29 | -0.20 |
| | *(0.54)* | *(2.57)* | *(6.87)* | *(3.33)* | *(2.29)* | *(2.47)* | *(1.58)* | *(-0.70)* |
| Carhart alpha | 0.23 | 0.47*** | 1.14*** | 0.91*** | 0.62*** | 0.40*** | 0.52*** | -0.10 |
| | *(1.13)* | *(3.22)* | *(9.08)* | *(3.82)* | *(2.85)* | *(2.83)* | *(2.86)* | *(-0.35)* |
| 5FF alpha | -0.02 | 0.14 | 1.03*** | 1.05*** | 0.34 | 0.09 | 0.50*** | -0.16 |
| | *(-0.10)* | *(1.08)* | *(7.68)* | *(4.30)* | *(1.59)* | *(0.67)* | *(2.64)* | *(-0.55)* |
| ***Panel B: All but micro breakpoints*** | | | | | | | | |
| VW return | 1.11*** | 1.73*** | 2.12*** | 1.01** | 1.84*** | 2.16*** | 1.15*** | -0.69 |
| | *(3.95)* | *(5.38)* | *(5.54)* | *(2.18)* | *(5.35)* | *(6.56)* | *(4.55)* | *(-1.61)* |
| CAPM alpha | 0.34* | 0.68*** | 0.79*** | 0.45 | 0.84*** | 0.68*** | 0.30** | -0.54* |
| | *(1.67)* | *(4.36)* | *(3.68)* | *(1.52)* | *(2.92)* | *(4.65)* | *(2.17)* | *(-1.69)* |
| 3FF alpha | 0.20 | 0.52*** | 1.01*** | 0.81*** | 0.65** | 0.72*** | 0.42*** | -0.23 |
| | *(0.99)* | *(3.35)* | *(4.74)* | *(2.73)* | *(2.27)* | *(4.97)* | *(2.98)* | *(-0.72)* |
| Carhart alpha | 0.23 | 0.56*** | 1.14*** | 0.91*** | 0.69** | 0.63*** | 0.44*** | -0.25 |
| | *(1.09)* | *(3.52)* | *(5.28)* | *(3.00)* | *(2.34)* | *(4.24)* | *(3.09)* | *(-0.77)* |
| 5FF alpha | 0.03 | 0.31** | 1.15*** | 1.12*** | 0.18 | 0.44*** | 0.28** | 0.10** |
| | *(0.17)* | *(2.08)* | *(5.28)* | *(3.76)* | *(0.67)* | *(3.23)* | *(1.97)* | *(-0.32)* |

### 4.6 Conclusion

In this chapter, I have empirically examined the interaction effect of product market competition and advertising intensity on stock returns. Using the sample of all public firms from 1977 to 2018 in the US market, this chapter tests how market structure affects the advertising-return relation, and whether advertising intensity influences the relationship between market competition and stock returns. Product market competition is measured by the Herfindahl-Hirschman Index (HHI) of Hou and Robinson (2006) and advertising intensity is defined as the ratio of advertising expenditure on sales. Following Gu (2016), the double sorting approach is used to examine the joint effect of advertising and competition industry and stock return. In particular, firms are divided into three portfolios based on the NYSE and all-but-micro breakpoints, whereas independently, I form three portfolios based on the rank of HHI index using all stocks. The interaction of HHI and AD/sale portfolios results in nine portfolios with different characteristics in competition degree and advertising intensity.

This chapter discovers that advertising is negatively related to stock return, and this association is stronger for firms in high competitive industries. In addition, consistent with Hou and Robinson (2006) and, Hashem and Su (2015) this chapter shows evidence that there is a positive correlation between industry competition and stock returns. This impact is more pronounced for firms with low advertising intensity, compared to companies in the high advertising intensity group. These results are robust when I use two subsample data periods, including 1977 to 1993 and 1996 to 2018. Furthermore, as a robustness check, an alternative index introduced by Hoberg and Phillips (2010) is used to measure product market competition. The original findings remain intact once I implement all robustness tests.

Following Chauvin and Hirschey (1993), advertising intensity are more likely to be high among toy companies and firms which provide education, and food and kindred products. In contrast, firms in heavy industry usually spend little for advertising. The industry effect suggests that large diversified firms are more broadly positioned to take advantage of scale advantages in advertising, whereas market value difference across smaller firms may simply be tied more closely to the fortunes of specific industries. Even the method of breakpoints allocation can control for microcap effect but it may lead to a potential industry-bias. However, the result of this chapter is still reliable due to the following reasons. First, Chauvin and Hirschey (1993) suggest that the impact of advertising on market value of firms is due to firm size. A dollar investing in advertising can bring a greater effect for relatively larger firms. Hence, advertising intensity, which is defined as the ratio of advertising expenditure over sale avenue, is used to measure firm's advertising in this chapter. Second, the results of this chapter are robust using two different methods of breakpoints for advertising intensity and two alternative measures of product market competition. Finally, the double sorting portfolio approach also eliminates the industry bias.

The findings of this chapter have important implications for not only academics but also practitioners. First, this chapter is one of the first studies to provide empirical evidence about the joint effect of product market competition and advertising on stock returns. It provides a valuable insight into the determinants of stock returns and also opens some avenues for future research. In particular, the empirical evidence shows the failure of asset pricing models in explaining stock returns, and suggests a requirement for an asset pricing model that considers features of advertising and product market competition as a determinant of asset returns. Researchers, who are interested in stock returns should carefully consider the effect of advertising and competition level when constructing a new asset pricing model. A more comprehensive model allows a superior prediction on expected returns of stocks. Second, firms in competitive markets may under-invest in advertising. This is because this chapter shows evidence that advertising is negatively correlated to stock returns, and this relation is stronger under the effect of market competition. This finding supports the positive causal effect of concentration on advertising of Chandra and Weiberg (2018). This observation is important in firm's management and managers should realize these potential joint effects of advertising and competition level on stock returns before investing in an advertising campaign.

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# CHAPTER 5: THE RELATION BETWEEN CSR AND STOCK PERFORMANCE. EVIDENCE FROM HURRICANE STRIKES

## 5.1 Introduction

Hurricane strikes or natural disasters in the general not only cause economic losses and fatalities but also disrupt the corporate operation, affect business conditions which have impacts on firms' performance. According to the Emergency Events Database (EM-DAT), 396 natural disasters were recorded, which lead to damage of around USD 103 billion in 2019 and an estimated 11,755 deaths over the world. Meanwhile, the US experiences 20 disasters with a result of a $29.767 billion loss in 2019 (CRED, 2020). Unfortunately, these events are mostly sudden, unpredictable, and unavoidable, thus they generate an exogenous shock to firms. As a result, previous literature studies extensively the response of corporate activities to the effect of exogenous shocks like natural disasters (see, e.g., Cavallo, Powell, and Becerra, 2010; Hsu, Lee, Peng, and Yi, 2018; He, 2019) and hurricanes specifically (Dessaint and Matray, 2017; Aretz, Banerjee, and Pryshchepa, 2018; Kruttli, Tran, and Watugala, 2019; Zivin, Lia, and Panassie, 2020). For instance, Aretz et al. (2018) show evidence that hurricane strikes prompt distressed firms to risk-shift and moderately distressed firms experience high failure rates after these events. He (2019) examines the relationship between credit demand shocks and bank lending, and economic activities of non-shocked firms. He finds that after natural disasters, banks are more likely to lend to the firms affected by the shock.

The increase in extreme weather and climate events have put the stakeholders' interests under public attention, which motivates academic and managerial interest in corporate social responsibility (CSR). According to the World Bank, CSR is defined as "the commitment of businesses to behave ethically and to contribute to sustainable economic development by working with all relevant stakeholders to improve their lives in ways that are good for business, the sustainable development agenda, and society at large" (Kitzmueller and Shimshack, 2012). Therefore, it is believed that CSR can add to firm value by positively shaping stakeholder perceptions (Deng, Kang, and Low, 2013). Nevertheless, prior studies show controversial evidence about the impact of CSR on firms' performance. On the one hand, CSR is argued to be correlated with agency problems and incentive issues (Jensen, 2002; Cheng, Hong, and Shue, 2019; List and Momeni, 2021). Meanwhile, other authors suggest that engagement in CSR enhances a firm's performance and market value (Servaes and Tamayo, 2013; Flammer, 2015; Lins, Servaes, and Tamayo, 2017; Shiu and Yang, 2017; Hsu, Lee, and Yi, 2018). For instance, Hsu, Lee, and Yi (2018) propose a model to show that CSR investment helps firms recover from natural disasters by enhancing customers' and employees' preferences. Some mechanisms have been given to explain the positive effects of CSR. First, CSR provides firms an opportunity to improve social image and brand awareness (Lev, Petrovits, and Radhakrishnan, 2009). According to Bhattacharya and Sen (2003), firms with high CSR get more loyal consumers than others. Lins, Servaes, and Tamayo (2017) also suggest that investment in social capital, measured by CSR, improves trust between firms and stakeholders, which then pay offs when there is a negative shock in the level of trust in corporations. Second, CSR engaging firms may enhance employee satisfaction, and thus attract talent and increase employees' effort and productivity (Shapiro and Stiglitz, 1994; Faleye and Trahan, 2011).

Due to the increase in the importance of CSR, this chapter examines whether CSR activities can protect firms against the negative exogenous shocks caused by hurricanes- one of the most harmful disasters. In particular, I study how stock return and liquidity respond to hurricane strikes when firms are located in the neighborhood of the disaster areas and test the insurance-like effects of CSR. The insurance-like effects refer to the situation in which CSR can mitigate drawbacks to firms' performance caused by the occurrence of a negative event, i.e. hurricane events (Shiu and Yang, 2017). We consider hurricane strikes (known as cyclones or typhoons) as an exogenous shock due to the following reason.  The occurrence of a hurricane contains no information about the probability of the next event in the near future and is exogenous to firms' characteristics (Dessaint and Matray, 2017). It declines the likelihood of unobserved heterogeneity and reserve causality problems. In addition, hurricanes cause heavy damage to the affected regions, and this impact decreases with the distance from the disaster location. As a result, it permits our propensity matching score procedure. Based on the preceding discussion, this chapter predict that hurricanes interrupt corporate activities, therefore causing a negative shock for stock performance of firms. However, firms with CSR engagement can suffer less due to the insurance-like effects of CSR. In order to test this hypothesis, we study the performance of a sample of 916 non-financial US firms with available CSR data on the MSCI ESG Stats database and hurricane data from the Spatial Hazard and Loss database over the time period of 1992-2012.

This chapter is linked to the idea of Hsu, Lee, and Yi (2018). They consider CSR as an intangible investment in stakeholder relationships and provide evidence that firms with high CSR get more stable sales and higher productivity post-disaster. I focus on one element of natural disasters-hurricanes and provide empirical evidence on the response of firms' stock performance. To track the hurricane event, I follow Dessaint and Matray (2017) by defining a dummy variable that is equal to one if the firm is located in a state that is affected by hurricane strikes and zero otherwise. In terms of CSR, the MSCI ESG Stats database provides information on firms' CSR, including strengths and concerns of different categories. As both elements can contribute to the effect of CSR on stock performance, I follow the method of Lins et al. (2017), which captures both strengths and concerns of each category to calculate the CSR score. To measure stock liquidity, this chapter considers several liquidity measures that are widely used in the literature including trading volume and the illiquidity ratio of Amihud (2002) - (the RtoV ratio). While trading volume provides the picture of aggregate funds' flow, it does not represent the price impact factor, which is why I also use the Amihud ratio as an alternative liquidity measure. I also employ two recently proposed price impact ratios, namely the return to turnover ratio (the RtoTR ratio) of Florackis et al. (2011) and the free float adjusted price impact ratio (the RtoTRF ratio) of Karim et al. (2016).

I first investigate the stock market reactions to the occurrence of hurricane strikes. A hurricane is costly for a firm as it can cause a loss in both economic and human resource, thus stakeholders may no longer be willing to deal with the firm during this period. As a result, I predict that firms affected by hurricanes may experience negative abnormal stock returns. Being consistent with this expectation, I find a significant mean cumulative abnormal return (CAR) computed using the CAPM of – 0.666% during the six-day window around the hurricane date. Using the Fama and French three-factor model gives a result of -0.669% (significant at the 1% level).

I next examine the effect of CSR on the abnormal return of firms located in the hurricane strikes area. After controlling for a variety of firm's characteristics, I find that CSR engagement is positively associated with abnormal returns of firms in hurricane-afflicted areas. I find large and significant positive effects of CSR on CAR(-1,5), CAR(-1,10), and CAR(-1,30). This finding holds when I employ different CSR measures and control for corporate governance. I also run the placebo tests in event dates of hurricane strikes for robustness. Specifically, I assign a new date before the hurricane date of each hurricane incident of my sample, then construct variables CAR(-30,-1), CAR(-10, -1), and CAR(-5,-1). I then run similar regressions to check whether CSR affects these cumulative abnormal returns. The findings indicate that the insurance-like effect of CSR is only under the occurrence of hurricane strikes.

I then apply the propensity score matching (PSM) procedure to address the possible endogeneity of hurricanes by matching firms hit by the disaster with firms that are not affected by the hurricane but sharing similar characteristics. This analysis is widely used in prior research (e.g., Rubin, 2001; Aretz, Banerjee, and Pryshchepa, 2018; Albuquerque, Koskinen, and Zhang, 2019). The results persist as I find that hurricanes negatively affect stock returns while there is a positive CSR and hurricane interaction effect on returns of stocks. In this section, I also check the impact of hurricanes and CSR on stock liquidity. Using different measures of stock liquidity, I find a positive effect of engaging in CSR on stock liquidity of hurricane-affected firms.

In addition, I conduct another test to obtain greater insight into the positive effect of CSR on stock return and stock liquidity by following Erhemjamts et al. (2013) and Dutordoir et al. (2018) to classify CSR into Strength and Concern components. I report a strong negative effect of Concerns and a positive impact of Strengths on stock performance. Given that some categories of CSR may contribute more in the effect of CSR on the stock performance of hurricane-affected firms, CSR is split into two components, namely those that communicate mainly to internal stakeholders (Employee Relations and Diversity) and those that speak mainly to external stakeholders (Community, Human Rights, and Environment). The estimated coefficients of the interaction term between CSR and hurricane suggests that the impact of CSR are mainly because of external components. I also consider the impact of both short term and long term CSR engagement on stock performance following Shiu and Yang (2017).

This chapter contributes to the literature in the following ways. First, it adds value to the literature strand that studies the impact of hurricanes on a firm's activities. Prior studies have focused on managers' behavior biases (Dessaints and Matray, 2017), industrial firms risk-shift (Aretz, Banerjee, and Pryshchepa, 2018), financial markets (Kruttli, Tran, and Watugala, 2019), and the housing market (Zivin, Liao, and Panassie, 2020). The chapter provides evidence for economic losses caused by hurricane landfalls by presenting the adverse effects of these disasters on shareholder value. This chapter also shows that after the hurricane event, stocks are more liquid and exhibit higher returns. Moreover, the chapter indicates the insurance-like effects of CSR activities on hurricane-affected firms. Firms engaging in CSR have less consequence in stock returns and stock liquidity from traumatic events such as hurricane strikes.

Another main contribution of this chapter is enhancing the growing body of research in the empirical evaluation of the relationship between CSR and firms' performance. There is recent empirical evidence concerning the positive effect of CSR engagement on firms' activities (Flammer, 2015; Shiu and Yang, 2017; Albuquerque, Koskinen, and Zhang, 2019). For example, Albuquerque et al. (2019) propose a model which predicts that CSR declines systematic risks and rises firms' value by increasing product differentiation. This chapter contributes to this literature by providing further evidence on the insurance-like effects of CSR on stock returns and stock liquidity for hurricane-inflicted companies. I show that in the face of exogenous events like hurricane strikes, firms investing in CSR have superior abnormal stock returns and higher liquid stocks.

The remainder of this chapter is organized as follows. Section 5.2 describes data and summary statistics. Section 5.3 presents the empirical results of the main econometric analysis. Robustness tests are reported in section 5.4. Section 5.5 concludes the chapter.

## 5.2 Data and Summary Statistics

### *5.2.1 Sample*

The initial sample consists of all public US firms listed on the NYSE, AMEX, and NASDAQ exchanges over the time period 1992 and 2012. I collect the financial and stock data from the COMPUSTAT and CRSP databases. This data is then combined with hurricane data and corporate social activity data.

My sample is from 1992 as the data of firms' CSR activities was incomplete before 1992, and it ended in 2012.

The sample of state-level hurricanes data is obtained from the SHELDUS (Spatial Hazard and Loss) Database, which is maintained by the University of South Carolina. For each incident, I acquire information on the start date, the end date, and the county location of main hurricane landfalls. A county is reported as an affected county in SHELDUS if there is monetary or human loss caused by a hurricane event and the subsequent rainfalls. Following Dessaint and Matray (2017), I only consider hurricanes with total direct damages above five billion dollars. I restrict my sample with hurricanes that occurred after 1991 to coincide with the availability of the CSR data. This selection leaves me with a total of 22 hurricanes over the period from 1992 to 2012. Table 5.1 lists all 22 hurricane landfalls during this period as well as the start date, the end date, and the counties affected by the disaster.

**Table 5.1: Sample Description**

Panel A describes the 22 natural disasters included in the sample over the 1992-2012 period. Names, start date, end date, number of affected counties, and the location of each natural disaster is obtained from the SHELDUS database at the University of South Carolina. The list is restricted to events classified as Major Disasters in SHELDUS, with total direct estimated damages above $1 billion 2007 constant dollars and lasting less than 30 days

**Panel A: List of major disasters in the U.S. territory over the 1992-2012 period**

| Disaster | Start date | End date | Number of affected counties | Affected Location |
|---|---|---|---|---|
| Hurricane Andrew | 23/08/1992 | 27/08/1992 | 51 | AL, FL, LA, MS |
| Hurricane Iniki | 11/9/92 | 12/9/92 | 1 | HI |
| Hurricane Alberto | 7/7/94 | 10/7/94 | 41 | AL, FL, GA |
| Hurricane Opal | 4/10/95 | 6/10/95 | 186 | AL, FL, GA, LA, MS, NC, SC |
| Hurricane Fran | 5/9/96 | 8/9/96 | 100 | NC, SC, VA, WV |
| Hurricane Bonnie | 27/08/1998 | 29/08/1998 | 43 | NC, VA |
| Hurricane Georges | 20/09/1998 | 29/09/1998 | 78 | AL, FL, LA, MS |
| Hurricane Floyd | 14/09/1999 | 16/09/1999 | 226 | CT, DC, DE, FL, MD, ME, NC, NH, NJ, NY, PA, SC, VA, VT |
| Hurricane Allison | 5/6/01 | 17/06/2001 | 77 | AL, FL, GA, LA, MS, PA, TX |
| Hurricane Isabel | 18/09/2003 | 19/09/2003 | 89 | DE, MD, NC, NJ, NY, PA, RI, VA, VT, WV |
| Hurricane Charley | 13/08/2004 | 14/08/2004 | 67 | FL, GA, NC, SC |
| Hurricane Frances | 3/9/04 | 9/9/04 | 311 | AL, FL, GA, KY, MD, NC, NY, OH, PA, SC, VA, WV |
| Hurricane Ivan | 12/9/04 | 21/09/2004 | 284 | AL, FL, GA, KY, LA, MA, MD, MS, NC, NH, NJ, NY, PA, SC, TN, WV |
| Hurricane Jeanne | 15/09/2004 | 29/09/2004 | 160 | DE, FL, GA, MD, NC, NJ, PA, SC, VA |
| Hurricane Dennis | 9/7/05 | 11/7/05 | 200 | AL, FL, GA, MS, NC |
| Hurricane Katrina | 25/08/2005 | 30/08/2005 | 288 | AL, AR, FL, GA, IN, KY, LA, MI, MS, OH, TN |
| Hurricane Rita | 20/09/2005 | 24/09/2005 | 123 | AL, AR, FL, LA, MS |
| Hurricane Wilma | 24/10/2005 | 24/10/2005 | 24 | FL |
| Hurricane Gustav | 25/08/2008 | 7/9/08 | 98 | AR, LA, MS |
| Hurricane Ike | 1/9/08 | 15/09/2008 | 163 | AR, LA, MO, TN, TX |
| Hurricane Irene | 21/08/2011 | 28/08/2011 | 40 | CT, MA, MD, NC, NJ, NY, VA, VT |
| Hurricane Sandy | 22/10/2012 | 2/11/12 | 274 | CT, DE, MA, MD, NC, NH, NJ, NY, OH, PA, RI, VA, WV |

I collect CSR data from the MSCI ESG Stats Database (formerly KLD), which is used extensively in the finance literature (see among others, Deng et al., 2013; Lins et al., 2017; Cheng et al., 2019; Chen, Dong, and Lin, 2020) and in studies examining insurance-like effects of CSR (Koh, Qian, and Wang, 2014; Zolotoy, O'Sullivan, and Chen, 2019). ESG Stats provides firm-level social ratings on environmental, social, and governance performance with 13 categories of large public firms in the period from 1991 to 2016. Even though the CSR data has been collected since 1991, it is incomplete until 1992, thus the chapter uses the data from 1992. Besides, after 2012, there are a lot of missing variables in terms of CSR's categories. Hence, my final sample covers the period from 1992 to 2012. In this chapter, I assess CSR ratings based on five categories, including community, diversity, employee relations, environment impact, and human rights. The product dimension of CSR is excluded out of the sample as most of the categories in this matter are considered as outside CSR's scope. I also do not include corporate governance in my main analysis as corporate governance category of KLD data differs from other categories (Hong, Kubik, and Scheinkman, 2012). There are also some concerns about whether it is measured in the traditional sense (Kruger, 2015) and governance is not a component of firm's CSR remit (Lins et al., 2017). However, I still control possible correlation between governance and the CSR score by including the governance category in my robustness check. The last six categories of the KLD rating, including alcohol, gambling, firearms, military, nuclear and tobacco are also not considered because they mainly belong to the industry rather than the firm level.

For each category, KLD data provides both strengths and concerns elements with "1" indicating that strength/concern is present and "0" signifying its absence. According to Lins et al. (2017) and Zolotoy, O'Sullivan, and Chen (2019), this chapter captures both strength and concern elements by adding strengths and subtracting concerns when calculating the CSR score. As the numbers of strengths and concerns of each category vary across years, I define the strength (concern) index of a firm in each year as the ratio of number of strengths (concerns) over the maximum possible strengths (concerns) in that category. The net CSR score in each category-year is then calculated by subtracting the concern index from the strengths index. The sum of the total of five net CSR scores gives us the main variable – *CSR score* for analysis.

To examine the impact of CSR on the stock performance of hurricane-afflicted firms, I collect daily data on stock returns, trading volume from CRSP, and accounting data from COMPUSTAT. To be included in the sample, a firm must have matching data in both databases. Following previous studies, I exclude financial firms with Standard Industrial Classification (SIC) between 6000 and 6999. Non-financial firms are then merged with the MSCI ESG Stats Database and hurricanes landfalls data. The final sample contains 916 firms that are affected by hurricane strikes.

In order to measure stock liquidity, I use several liquidity measures, including trading volume, the illiquidity ratio of Amihud (2002), the return to turnover ratio of Florackis et al. (2011), and the free float adjusted price impact ratio by Karim et al. (2016). First, trading volume is a straightforward proxy of liquidity. It is calculated as the amount of traded shares between market makers in buying and selling activities for security i at time period t. Trading volume is usually calculated as dollar trading volume with the following formula:

$$DVol_{it} = \sum_{j=1}^{n} P_{idt} \ x \ Vol_{idt} \tag{5.1}$$

Where $DVol_{it}$ is the trading volume of security i over time period t. It is calculated as the sum of the dollar value of $n$ transactions of stock i at time period t. $P_{idt}$ and $Vol_{idt}$ are price and quantity of stock i for trading day d at time period t, respectively. This measure is frequently used in prior studies such as Brennan, Chordia, and Subrahmanyam (1998), Chordia, Subrahmanyam, and Anshuman (2001), O’Hara (2003), and Becker-Blease and Paul (2006).

While trading volume captures the amounts of transactions, I also compute alternative liquidity measures that capture the price impact dimension of stock liquidity. A well-known ratio is the illiquidity ratio of Amihud (2002). In particular, this illiquidity ratio reflects the sensitivity of average absolute daily price to $1 trading volume for a stock, it is also referred to as the return to volume ratio. The average of daily impacts over a sample period is calculated as follows:

$$RtoV_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{Dvol_{idt}} \tag{5.2}$$

Where $RtoV_{it}$ is the illiquidity ratio of stock i over time period t, $D_{it}$ is the number of trading days in time period t for stock i, $R_{idt}$ is the return of stock i on day d in the time period t, and $Dvol_{idt}$ is the dollar volume of stock i on day d in the time period t. The stock is said to be illiquid if the return to volume RtoV ratio is high. As $RtoV_{it}$ measures illiquidity, stocks with high Amihud ratios are more illiquid, so we multiply it with minus one to convert the ratio into a liquidity ratio.

In addition, I employ two recently proposed price impact ratios to measure liquidity, including the return to turnover ratio (RtoTR) of Florackis et al. (2011) and free float adjusted ratio (RtoTRF) of Karim et al. (2016) with the following formulas:

$$RtoTR_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TR_{idt}} \tag{5.3}$$

Where $RtoTR_{it}$ is the return to turnover ratio of stock i over time period t, $D_{it}$ is the number of valid trading days of security i over time t, $R_{idt}$ is the daily return of security i in day d, and $TR_{idt}$ is the turnover ratio of security i in day d.

$$RtoTRF_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|R_{idt}|}{TRF_{idt}} \tag{5.4}$$

Where $RtoTRF_{it}$ is the return to turnover ratio adjusted with the public free float factor of stock i over time period t, $D_{it}$ is the number of available trading days for security i for the period of time t, $R_{idt}$ is daily return of stock i, and $TRF_{idt}$ is the corresponding turnover ratio captured by the free float percentage. $TRF_{idt}$ is calculated as trading volume divided by the multiplication of the number of share outstanding and the public free float factor.

Following Florackis et al. (2011), the *RtoTR* ratio not only inherits the benefits of the Amihud ratio but also overcomes the size bias drawbacks of the Amihud ratio. Meanwhile, the *RtoTRF* ratio is superior because it captures the real supply of available stocks to the public for trading. Similarly, we also multiple *RtoTR* and *RtoTRF* with minus one to covert the ratios into liquidity rather than illiquidity measures.

Other risk factors such as market risk, size, value, momentum, investment opportunities, and profitability are obtained from the Kenneth R.French online library[14]. I employ stock raw returns and abnormal returns to measure stock performance of firms. To test our main hypotheses, this chapter relies on the sample of firms that experience hurricane events and invest in CSR. I also control for firm characteristics that are shown to affect firm performance and stock performance such as market capitalization, leverage, R&D, investment, stock volatility, and firm age. Detailed variable definitions are reported in the Appendix.

*5.2.2 Summary Statistics*

Table 5.2 shows the descriptive statistics for the main firm-year variables. Panel A displays the statistics of variables while their correlation matrix is reported in Panel B. CSR score is negative with the mean value of -0.093, and the median value is -0.063. Thus, on average, firms have less strengths than concerns. This finding is consistent with the prior research of Servaes and Tamayo (2013), and Lins et al. (2017). The mean (median) value of firm size is 6.99

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[14] http://mba.tuck.dartmouth.edu/pages/faculty/Ken.French/data library.html

(6.785). The values of leverage, return to asset ratio (ROA), and Tobin's Q are 0.218 (0.182), 0.170 (0.132), and 2.067 (1.573) respectively.

**Table 5.2: Summary Statistics**
Table shows the summary statistics of the main variables in my study and their correlation matrix. Detailed descriptions of variables are reported in the Appendix.

**Panel A: Summary Statistics**

| | **No. of Obs.** | **Mean** | **Std Dev** | **p10** | **p50** | **p90** |
|---|---|---|---|---|---|---|
| CSR | 916 | -0.093 | 0.451 | -0.667 | -0.063 | 0.333 |
| Firm Size | 916 | 6.990 | 1.622 | 5.039 | 6.785 | 9.201 |
| Leverage | 916 | 0.218 | 0.216 | 0.000 | 0.182 | 0.483 |
| ROA | 916 | 0.107 | 0.187 | -0.006 | 0.132 | 0.247 |
| Tobin's Q | 916 | 2.067 | 1.512 | 0.943 | 1.573 | 3.724 |
| R&D | 916 | 0.498 | 0.500 | 0.000 | 0.000 | 1.000 |
| Dividend | 916 | 0.480 | 0.500 | 0.000 | 0.000 | 1.000 |
| Log (Firm Age) | 916 | 2.703 | 0.960 | 1.386 | 2.773 | 3.871 |

**Panel B: Correlation Matrix**

| | CSR | Firm Size | Leverage | Cash Holdings | ROA | Tobin's Q | R&D | Dividend | Log (Firm Age) |
|---|---|---|---|---|---|---|---|---|---|
| CSR | 1.000 | | | | | | | | |
| Firm Size | 0.361 | 1.000 | | | | | | | |
| Leverage | 0.007 | 0.252 | 1.000 | | | | | | |
| Cash Holdings | -0.107 | -0.449 | -0.278 | 1.000 | | | | | |
| ROA | 0.119 | 0.301 | -0.052 | -0.489 | 1.000 | | | | |
| Tobin's Q | 0.047 | -0.311 | -0.193 | 0.523 | -0.213 | 1.000 | | | |
| R&D | 0.027 | -0.074 | -0.147 | 0.362 | -0.219 | 0.211 | 1.000 | | |
| Dividend | 0.191 | 0.335 | 0.108 | -0.283 | 0.206 | -0.087 | -0.092 | 1.000 | |
| Log (Firm Age) | 0.180 | 0.409 | 0.035 | -0.225 | 0.130 | -0.155 | 0.078 | 0.319 | 1.000 |

## 5.3 Empirical Results

### *5.3.1 The impact of hurricanes on stock return*

This section examines the effect of hurricane strikes on shareholder wealth using standard event study methodology and consider the first day when the hurricane hits a county in which firm headquarters is located. The event date is the beginning day of the landfall following the SHELDUS database. The abnormal stock returns are calculated using CAPM, Fama and French (1993) three-factor model, and Carhart (1997) four-factor model. The CAPM model parameters are estimated using 260 trading days of return data ending 11 days before the hurricane strike date, using the CRSP value-weighted (equal-weighted) return as a proxy for the market return. The daily abnormal stock returns are cumulated to obtain the CAR from day t1 before the hurricane strike date to day t2 after the hurricane strike date. The three factors used in the Fama-French (1993) three-factor model are CRSP value-weighted index, SMB (daily return difference between the returns on the small and large size portfolios), and HML (daily return difference between the returns on the high and low book- to-market-ratio portfolios). The four factors used in the Carhart (1997) model are CRSP value-weighted index, SMB, HML, and UMD (daily return difference between the returns on the high and low prior return portfolios). I then aggregate daily abnormal returns by averaging them over all firm-hurricane pairs, and summing them over the trading days of different event windows, including [-1,5], [-1,10], and [-1,30] to compute the cumulative abnormal return (CAR). I estimate statistical significance using the Wilcoxon signed-rank test (Kamiya et al., 2020.)

**Table 5.3: The Effect of Hurricane on Shareholder Value**

This table presents the mean and median cumulative abnormal returns (CARs) for firms surrounding hurricane strike dates. The abnormal stock returns are calculated using the market model, Fama-French (1993) three-factor model, and the Carhart (1997) four-factor model, respectively. The market model parameters are estimated using 260 trading days of return data ending 11 days before the hurricane strike date, using the CRSP value-weighted (equal-weighted) return as a proxy for the market return. The daily abnormal stock returns are cumulated to obtain the CAR from day $t_1$ before the hurricane strike date to day $t_2$ after the hurricane strike date. The three factors used in the Fama-French (1993) three-factor model are CRSP value-weighted index, SMB (daily return difference between the returns on small and large size portfolios), and HML (daily return difference between the returns on high and low book-to-market-ratio portfolios). The four factors used in the Carhart (1997) four-factor model are CRSP value-weighted index, SMB, HML, and UMD (daily return difference between the returns on high and low prior return portfolios). The numbers in parentheses are $p$ -values for $t$ -tests that the mean CAR is equal to zero and $z$ -values for Wilcoxon signed-rank test that the median CAR is equal to zero, respectively. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | **CAPM** | | | | **Three- and Four-Factor Models** | | | |
|---|---|---|---|---|---|---|---|---|
| | **Value-weighted** | | **Equal-weighted** | | **Fama-French three-factor model** | | **Carhart four-factor model** | |
| **CARs (%)** | **Mean** | **Median** | **Mean** | **Median** | **Mean** | **Median** | **Mean** | **Median** |
| CAR (-1, 5) | -0.666*** | -0.506*** | -0.712*** | -0.580*** | -0.669*** | -0.712*** | -0.648*** | -0.706*** |
| | (0.009) | (-2.587) | (0.006) | (-2.903) | (0.010) | (-3.347) | (0.010) | (-3.379) |
| CAR (-1, 10) | -0.845*** | -0.706*** | -0.904*** | -0.818*** | -0.865*** | -0.886*** | -0.832*** | -0.895*** |
| | (0.008) | (-3.429) | (0.004) | (-2.559) | (0.005) | (-2.634) | (0.010) | (-2.955) |
| CAR (-1, 30) | -1.107*** | -0.931** | -1.251*** | -0.957*** | -1.011*** | -1.037*** | -1.150*** | -1.209*** |
| | (0.009) | (-2.034) | (0.005) | (-2.667) | (0.009) | (-2.873) | (0.007) | (-3.188) |

The mean and median values of abnormal returns for various event windows are reported in Table 3. The mean (median) CAR (-1,5), CAR (-1,10), and CAR (-1,30) computed using the CAPM model and the CRSP value-weighted index return are -0.666% (-0.506%), -0.845% (-0.706%), and -1.107% (-0.931%), respectively, all of which are significant at 1% level. Similar patterns are seen when using equal-weighted index return but with larger magnitude. The results remain intact when I use the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. All abnormal returns are negative and statistically significant at 1% level.

*5.3.2 The insurance-like effect of CSR on stock return*

This section examines the effect of CSR on stock return by presenting multivariate regressions using CAR as the dependent variable and the CSR score as the key explanatory variable. The abnormal returns are calculated using the CAPM model. In addition to control variables discussed in section 5.2, I add dummy variables of year and industry fixed effects to control for unobserved year and industry heterogeneity. We estimate the following regression:

$$CAR_{i,t+1} = \beta_0 + \beta_1 CSR_{i,t} + \gamma X_{i,t} + Industryfixedeffect + Yearfixedeffect + \varepsilon_{i,t+1} \quad (5.5)$$

where *CAR* is the cumulative abnormal return, we estimate the value of CAR for event windows [-1, -5]; [-1, -10]; [-1, -30]. *CSR* is the CSR score and *X* ix a vector of control variables. $\varepsilon$ is an error term.

**Table 5.4: The Effect of CSR on Shareholder Value**

This table presents the regression results for the relation between corporate social responsibility score and shareholder value. The dependent variable in models are the cumulative abnormal return (CAR) of hurricane-struck firms from 1 day before to 5 days after the hurricane strike date in columns (1) and (2), the cumulative abnormal return (CAR) of hurricane-struck firms from 1 day before to 10 days after the hurricane strike date in columns (3) and (4), and the cumulative abnormal return (CAR) of hurricane-struck firms from 1 day before to 30 days after the hurricane strike date in columns (5) and (6). The abnormal return is calculated using the market model. The market model parameters are estimated using 260 trading days of return data ending 11 days before the hurricane strike date. The CRSP value-weighted return is used as a proxy for the market return. The Appendix gives the definitions of all the variables. All regressions include year and industry fixed effects. Industry effects are based on two-digit SIC codes. Standard errors reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustering at the firm level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| | **CAR (-1,5)** | | **CAR (-1,10)** | | **CAR (-1,30)** | |
|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| CSR | 0.014*** | 0.014*** | 0.017*** | 0.017*** | 0.020*** | 0.021*** |
| | (0.004) | (0.004) | (0.005) | (0.005) | (0.007) | (0.007) |
| Firm Size | | 0.002 | | 0.001 | | 0.002 |
| | | (0.002) | | (0.002) | | (0.004) |
| Leverage | | 0.013 | | 0.026 | | 0.033 |
| | | (0.014) | | (0.016) | | (0.023) |
| Cash Holdings | | -0.006 | | -0.020 | | 0.000 |
| | | (0.018) | | (0.020) | | (0.029) |
| ROA | | -0.031** | | -0.042** | | -0.080*** |
| | | (0.016) | | (0.019) | | (0.027) |
| Tobin's Q | | -0.000 | | -0.002 | | -0.001 |
| | | (0.002) | | (0.002) | | (0.003) |
| R&D | | -0.009 | | -0.011 | | -0.012 |
| | | (0.008) | | (0.009) | | (0.013) |
| Dividend | | 0.002 | | 0.006 | | 0.003 |
| | | (0.006) | | (0.007) | | (0.011) |
| Log (Firm Age) | | -0.005* | | -0.003 | | -0.009 |
| | | (0.003) | | (0.004) | | (0.006) |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Obs. | 916 | 916 | 916 | 916 | 916 | 916 |
| Adjusted $R^2$ | 0.102 | 0.112 | 0.097 | 0.110 | 0.086 | 0.104 |

The results are reported in Table 5.4. Column (1) and (2) show the estimates of the model that employs the CAR (-1,5) - the cumulative abnormal return (CAR) of hurricane-struck firms from 1 day before to 5 days after the hurricane strike date as the dependent variable. T-statistics are calculated using standard errors adjusted for heteroscedasticity and firm level cluster. Results of CAR (-1, 10) are presented in columns (3) and (4), columns (5) and (6) are for CAR (-1, 30). In regression (5.1), I include only the CSR score in the addition year and industry fixed effects. I find a positive and strong significant relation (at the 1% level) between CSR and CAR (-1,5) of firms. The coefficient of 0.014 suggests that hurricane-afflicted firms engaging in CSR obtain 1.4 percentage points higher CAR (-1,5) then those without CSR activities. In column (2), I include some firms' characteristics such as firm size, leverage and ROA as control variables. The estimates show that ROA and firm age are negatively correlated to the CAR of firms, whereas the coefficient of the CSR score is unchanged. These results suggest that the positive effect of CSR on abnormal returns of hurricane-afflicted firms persists after controlling for firm characteristics. Similar findings are seen when I repeat the regressions using CAR (-1,10) and CAR (-1,30) as dependent variables. For instance, column (6) indicates that the cumulative abnormal return of hurricane-struck firms from 1 day before to 30 days after the hurricane strike date with CSR engagement is 2.1 percentage points higher than that of firms without CSR.

In summary, even after controlling for various firm characteristics, shareholders of hurricane-afflicted firms with high CSR realize higher return than those with low CSR[15].

*5.3.3 The CSR effects on Hurricane-Stock Performance*

In this section, I investigate the insurance-like effect of CSR on stock performance during the shock of hurricane strikes using the propensity score matching (PSM) procedure. There is a concern related to the location of hurricane. Some locations are more likely to be hit by hurricane strikes, and thus firms located in hurricane areas may possess different characteristics which drive the positive effect of CSR on stock performance, compared to firms that are not affected by the hurricane. To control for this potential selection bias, I follow Drucker and Puri (2005), among others, to estimate an average treatment effect of hurricane on firms by creating a sample of hurricane-afflicted firms (treated) and hurricane-non affected firms (control)

[15] In untabulated tests, I estimate the similar regressions using CAR calculated from Fama and French (1993) three-factor model and Carhart (1997) four-factor model for comparison. The findings are similar.

sharing the similar characteristics. I then test the effect of CSR on stock liquidity and stock return by estimating the following regression model:

$$Liquidity_{i,t} = \beta_0 + \beta_1 Hurricane_t + \beta_2 CSR_{i,t} + \beta_3 Hurricane_t \, x \, CSR_{i,t} + \gamma X_{i,t-1} + Industryfixedeffect + \varepsilon_{i,t} \quad (5.6)$$

Where $Liquidity_{i,t}$ represents one of four liquidity measures including trading volume, the RtoV, RtoTR, and RtoTRF price impact ratios. $Hurricane_t$ is a dummy variable equal to one for firms that are located in a hurricane-struck county over the period after the hurricane, and zero for the treatment firms before the hurricane and all the control firms. $\boldsymbol{X}_{i,t-1}$ is a vector of control variables including some firm's characteristics and four factor loadings based on the Carhart (1997) model (excess return on the market, size, market-to-book value, and momentum factor). To calculate factor loading, I first collect these factor returns from Kenneth French's website, and then estimate the factor loadings over the 60 month rolling window. Factor loadings are re-estimated each month. Past returns are shown to be correlated with current stock return thus, the results are controlled for *momentum* (the average of firm raw return over the past 12 months). Goyal and Santa-Clara (2003) show that stock price volatility may also affect returns, thus this chapter controls for firm's *Idiosyncratic risk* which is calculated as the cross-sectional equal-weighted average of the variances of all stock traded in that month.

In all models, I include industry fixed effect (defined at two-digit SIC code) as some industries may be more likely to invest in corporate social activities. All standard errors reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustering at the firm level. The coefficient on the interaction between CSR and hurricane captures the differential impact of CSR on monthly stock returns during the shock of the hurricane strike after controlling for the firm's factor loadings, financial characteristics, and industry fixed effects.

$$Return_{i,t} = \beta_0 + \beta_1 Hurricane_t + \beta_2 CSR_{i,t} + \beta_3 Hurricane_t \, x \, CSR_{i,t} + \gamma X_{i,t-1} + Firm\ fixed\ effect + Year\ fixed\ effect + \varepsilon_{i,t} \quad (5.7)$$

where $Return_{i,t}$ is the monthly raw return or the monthly market abnormal return. $CSR_{i,t}$ Is the CSR score of firm i at time period t. Other variables are defined as previously.

The results for both equations are presented in Table 5.5, in which estimated results of equation (5) are shown in columns (1)-(8) of Panel A and columns (1)-(4) of Panel B display the results of equation (6).

Table 5.5 Panel A tests whether firms with high CSR score have higher stock liquidity during the occurrence of hurricane strikes. Columns (1) and (2) show results of trading volume, the results of the RtoV ratio are presented in columns (3) and (4), and columns (5)-(6) and columns (7)-(8) show the estimates of the RtoTR and RtoTRF ratios, respectively. According to columns (1) and (2), I find a positive and significant coefficient of the interaction term between hurricane and CSR of 0.04 when using trading volume as a liquidity measure. This indicates that one-standard-deviation of the interaction term leads to a 4 % point increase in trading volume of hurricane-affected firms with CSR. When employing the RtoV ratio to measure stock liquidity, the coefficients of interaction term are 0.105 for the regression without the control variables and 0.115 for the regression with the control variables as shown in columns (3) and (4). All results are statistically significant at the 1% level.

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**Table 5.5: The Effect of CSR on the Hurricane-Stock Performance Relationship**

This table presents the regression results for the effect of CSR on the hurricane-stock performance relationship. Columns (1) to (4) present the results for stock return and columns (5) to (8) for stock liquidity. Stock return and liquidity data are obtained from CRSP. *Raw Return* is the monthly raw return. *Abnormal Return* is the monthly market-model adjusted return. *Trading Volume* is the raw trading volume in US dollars. *RtoV* is the Amihud illiquidity multiplied by minus one, where Amihud illiquidity is computed as the monthly average of the daily ratio of absolute value of stock return divided by dollar trading volume multiplied by one million. *RtoTR* and *RtoTRF* is the return to turnover ratio and price impact adjusted free float factor multiplied by minus one, respectively. *Hurricane* is a dummy variable equal to one for firms that located in a hurricane-struck county over the period after the hurricane, and zero for the treatment firms before the hurricane and for all the control firms. The characteristics based on market data (momentum, size, market-to-book, factor loadings) are updated monthly. Factor loadings are re-estimated each month based on the previous 60 months' data. The Appendix gives the definitions of all the variables. All regressions include year and industry fixed effects. Industry effects are based on two-digit SIC codes. Standard errors reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustering at the firm level. Appendix give definition of all variables. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: Stock liquidity**

| | **Trading Volume** | | **RtoV** | | **RtoTR** | | **RtoTRF** | |
|---|---|---|---|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** | **(7)** | **(8)** |
| Hurricane | -0.001 | -0.004* | -0.080*** | -0.076*** | -0.012* | 0.012 | 0.001 | 0.001 |
| | (0.003) | (0.004) | (0.012) | (0.012) | (0.007) | (0.015) | (0.009) | (0.009) |
| CSR | 0.110*** | 0.027*** | -0.148*** | 0.070*** | 0.009 | 0.011 | -0.008 | -0.006 |
| | (0.005) | (0.004) | (0.016) | (0.014) | (0.016) | (0.017) | (0.010) | (0.011) |
| Hurricane*CSR | 0.040*** | 0.040*** | 0.105*** | 0.115*** | 0.032*** | 0.026*** | 0.014** | 0.013** |
| | (0.014) | (0.011) | (0.027) | (0.032) | (0.010) | (0.009) | (0.007) | (0.006) |
| Ln (Market Cap) | | 0.087*** | | -0.212*** | | 0.001 | | -0.001 |
| | | (0.002) | | (0.010) | | (0.005) | | (0.003) |
| Long-Term Debt | | -0.058*** | | 0.202** | | 0.067 | | -0.014 |
| | | (0.004) | | (0.101) | | (0.041) | | (0.026) |
| Short-Term Debt | | 0.032* | | 0.545 | | -0.226* | | -0.132* |
| | | (0.019) | | (0.631) | | (0.120) | | (0.078) |
| Cash Holdings | | -0.022*** | | -0.126* | | 0.046 | | -0.016 |
| | | (0.004) | | (0.065) | | (0.043) | | (0.026) |
| Profitability | | -0.069*** | | -0.183*** | | 0.016 | | -0.011 |
| | | (0.007) | | (0.060) | | (0.044) | | (0.026) |
| Book-to-Market | | 0.021*** | | 0.394*** | | 0.003 | | 0.004 |
| | | (0.003) | | -0.089 | | (0.007) | | (0.005) |
| Negative B/M | | 0.052*** | | 0.289*** | | -0.064 | | 0.007 |
| | | (0.007) | | -0.109 | | (0.050) | | (0.033) |
| Momentum | | -0.026*** | | -0.260** | | 0.039 | | -0.003 |
| | | (0.007) | | (0.109) | | (0.045) | | (0.030) |
| Idiosyncratic Risk | | 0.228 | | -0.169 | | 0.191 | | -0.028 |
| | | (0.101) | | (0.332) | | (0.244) | | (0.160) |
| Four-Factor Loadings | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Obs. | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 |
| Adjusted $R^2$ | 0.202 | 0.482 | 0.016 | 0.088 | 0.202 | 0.0012 | 0.016 | 0.0011 |

**Table 5.5 (Continue)**

**Panel B: Stock return**

| | **Raw Return** | | **Abnormal Return** | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| Hurricane | -0.004*** | -0.004*** | -0.003** | -0.003** |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| CSR | 0.000 | 0.004** | -0.001 | 0.002 |
| | (0.002) | (0.002) | (0.001) | (0.001) |
| Hurricane*CSR | 0.010*** | 0.011*** | 0.007*** | 0.008*** |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Ln (Market Cap) | | -0.003*** | | -0.003*** |
| | | (0.001) | | (0.001) |
| Long-Term Debt | | 0.004 | | 0.008 |
| | | (0.006) | | (0.005) |
| Short-Term Debt | | -0.023 | | -0.015 |
| | | (0.023) | | (0.022) |
| Cash Holdings | | 0.019*** | | 0.015*** |
| | | (0.006) | | (0.005) |
| Profitability | | 0.007 | | 0.011 |
| | | (0.007) | | (0.007) |
| Book-to-Market | | 0.010*** | | 0.006* |
| | | (0.004) | | (0.003) |
| Negative B/M | | 0.012 | | -0.001 |
| | | (0.009) | | (0.008) |
| Momentum | | -0.017** | | -0.004 |
| | | (0.008) | | (0.008) |
| Idiosyncratic Risk | | -0.069 | | -0.037 |
| | | (0.044) | | (0.040) |
| Four-Factor Loadings | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes |
| No. of Obs. | 35,909 | 35,909 | 35,909 | 35,909 |
| Adjusted $R^2$ | 0.004 | 0.011 | 0.003 | 0.007 |

Similar findings are seen when liquidity is measured by the RtoTR and RtoTRF ratios. Following column (6), the interaction term between CSR and the RtoV ratio is 0.026 and statistically significant at the 1% level. Meanwhile, when using the RtoRTF ratio to proxy for stock liquidity, the estimated coefficients of interest are still positive but only significant at the 5% level. Moreover, cash holdings, momentum, and profitability are found to be negatively associated with stock liquidity.

Table 5.5 Panel B estimates the relationship between raw stock return, hurricanes, CSR, and the interaction of hurricanes and CSR only. The results are shown in column (1). According to Lins et al. (2017), to address the possible omitted variable issue, I then add a list of control variables for firm's financial health including cash holding, short term, long term debt, and profitability, and repeat the regression in column (2). I also control for some firms' characteristics, which are correlated to stock returns such as firm size, book-to-market ratio, dummy variable negative book-to-market, and firms' Idiosyncratic risk (the residual variance from the market model estimated over the 12 month-period before the hurricane start date, using monthly data). The results of both columns indicate that hurricanes negatively affect stock returns, and high CSR-firms exhibit superior stock performance during the shock of hurricane landfalls. In particular, the occurrence of hurricanes leads to a 0.4% decline in raw stock return of firms. The coefficient of 0.010 on the Hurricane-CSR interaction suggests that a one-standard-deviation increases in CSR is associated with a 1.00 percent point higher return during the occurrence of hurricane strikes. This finding persists even after controlling for several firm's characteristics such as market capitalization, long-term debt, short-term debt, and cash holdings, and four factor loadings.

Columns (3) and (4) show similar patterns when employing the abnormal return as the dependent variable. The coefficients of the interaction effect of CSR and hurricanes are positive and statistically significant at the 1% level. This result suggests that hurricane-period returns of stock increase with CSR activities. In terms of the control variables, market capitalization and momentum are negatively associated with stock return, whereas there is a positive and significant effect of cash holding on stock return.

### 5.4 Robustness

#### *5.4.1 Robustness check for insurance-like effects of CSR*

In this section, I run some robustness checks to verify that the positive effect of CSR on stock return of hurricane-affected firms are not driven by other characteristics rather than CSR itself. First, I am going to test whether my results are sensitive to the CSR measure by using an alternative measure of CSR. I repeat the tests of Table 5.4 but instead of the *CSR score* as above, I create a *raw CSR* variable. The *CSR score* is calculated by adding strength index and subtracting concerns index. In which, strength (concern) index is defined as of a firm in each year as the ratio of number of strengths (concerns)- strengths (concerns) scores over the maximum possible strengths (concerns) in that category. Meanwhile, the *raw CSR* is defined as the net CSR score computed by subtracting the concerns scores from strengths scores for all the five dimensions.

The results are shown in Panel A of Table 5.6. To conserve space, I report only the estimated coefficients of the main variables of interest. The coefficients of *Raw CSR* are all positive and statistically significant at the 1% level for various event windows. For example, the estimate of raw CSR when using CAR (-1,10) as the dependent variable is 0.005. This implies that there is a 0.5 percentage point higher of stock return of hurricane-affected firms with CSR activities, compared to those without CSR engagement.

In Table 5.6 Panel B, I further test our findings controlling for corporate governance. In this analysis, I use the *CSR score* to measure CSR and a range of governance measures in addition to other control variables in Table 5.4. *Board Independence* (fraction of board consisting of outside directors), *Board Size* (total number of members of the board of directors), and *Board Ownership* (fraction of outstanding shares owned by board members) are obtained from the MSCI Directors database. The estimated coefficients of CSR of three models are all positive and statistically significant at the 1% level. For instance, in column (3), the coefficient of CSR is 0.033, which indicates that firms engaging in CSR activities get a 3.3% point higher than others in the cumulative abnormal return (CAR) from 1 day before to 30 days after the hurricane strike date.

Meanwhile, the measures of governance are not significant except for the case of Board Size and Board Ownership when regressed using CAR (-1,5) as the dependent variable. In particular, column (1) shows that board size is negatively correlated to stock return (estimated coefficient equal to -0.047), whereas the fraction of outstanding shares owned by board members have a positive effect on stock return (estimated coefficient equal to 0.037). These findings suggest that the CSR effect on firms affected by hurricane landfalls persist when we control for governance impacts.

**Table 5.6: The Effect of CSR on Shareholder Wealth - Robustness Checks**

This table presents the results of robustness tests for the relation between CSR and shareholder value. Panel A presents the results using alternative measure of CSR. *Raw CSR* is the net CSR score computed by subtracting the concerns scores for all the five dimensions from the strength scores (CSR). Panel B presents the regression results of CSR on shareholder value and add measures of corporate governance. *Board Independence* (fraction of board consisting of outside directors), *Board Size*, a dummy of *CEO Duality*, and *Board Ownership* (fraction of outstanding shares owned by board members) are obtained from the MSCI Directors database. Panel C presents the result of placebo tests for the relation between CSR score and shareholder value. The dependent variables in Panel C are the cumulative abnormal return (CAR) of hurricane-struck firms from 30 days before to 1 day after the hurricane strike date in column (1), the cumulative abnormal return (CAR) of hurricane-struck firms from 10 days before to 1 day after the hurricane strike date in column (2), and the cumulative abnormal return (CAR) of hurricane-struck firms from 5 days before to 1 day after the hurricane strike date in column (3). The abnormal return is calculated using the market model. The market model parameters are estimated using 260 trading days of return data ending 11 days before the hurricane strike date. The CRSP value-weighted return is used as a proxy for the market return. The Appendix gives the definitions of all the variables. All regressions include year and industry fixed effects. Industry effects are based on two-digit SIC codes. Standard errors reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustering at the firm level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| **Panel A: Alternative CSR Measure** | | | |
|---|---|---|---|
| | **CAR (-1,5)** | **CAR (-1,10)** | **CAR (-1,30)** |
| | **(1)** | **(2)** | **(3)** |
| Raw CSR | 0.004*** | 0.005*** | 0.006** |
| | -0.002 | -0.002 | -0.003 |
| Control Variables of Table 5.4 | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |
| No. of Obs. | 916 | 916 | 916 |
| Adjusted $R^2$ | 0.11 | 0.109 | 0.102 |

| **Panel B: Controlling for Corporate Governance** | | | |
|---|---|---|---|
| | **CAR (-1,5)** | **CAR (-1,10)** | **CAR (-1,30)** |
| | **(1)** | **(2)** | **(3)** |
| CSR | 0.026*** | 0.028*** | 0.033*** |
| | -0.005 | -0.007 | -0.009 |
| Board Independence | 0.036 | 0.018 | 0.037 |
| | -0.027 | -0.04 | -0.06 |
| Board Size | -0.047* | -0.014 | 0.001 |
| | -0.024 | -0.038 | -0.04 |
| CEO Duality | 0 | -0.002 | 0.003 |
| | -0.009 | -0.01 | -0.014 |
| Board Ownership | 0.037** | 0.012 | -0.006 |
| | -0.017 | -0.023 | -0.031 |
| Control Variables of Table 5.4 | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |
| No. of Obs. | 451 | 451 | 451 |
| Adjusted $R^2$ | 0.186 | 0.192 | 0.172 |

| **Panel C: Placebo Test** | | | |
|---|---|---|---|
| | **CAR (-30,-1)** | **CAR (-10,-1)** | **CAR (-5,-1)** |
| | **(1)** | **(2)** | **(3)** |
| CSR | 0.008 | 0.001 | 0.005 |
| | -0.006 | -0.005 | -0.004 |
| Control Variables of Table 5.4 | Yes | Yes | Yes |
| Year Fixed Effects | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes |
| No. of Obs. | 916 | 916 | 916 |
| Adjusted $R^2$ | 0.103 | 0.095 | 0.071 |

Furthermore, I control for time-invariant omitted risk factors, by performing a placebo test to examine whether my results are robust. In particular, I assign abnormal return variables with new different event window [-30, -1]; [-10, -1]; and [-5, -1] before the hurricane date. I then run the same regression as in Table 5.4 and present results in Panel C of Table 5.6. Interestingly, I do not observe any significant effects of CSR on cumulative abnormal return. Specifically, the coefficients of CSR are positive but statistically insignificant at all columns when using CAR for different event windows. This finding suggests that the positive effect of CSR on stock return occurs only after the occurrence of hurricane strikes, not before.

In sum, the results of Table 5.6 highlight the positive impact of CSR engagement on stock return of hurricane-affected firms, even after controlling for the CSR measure and corporate governance. It also suggests that this effect exists only after hurricane landfalls.

*5.4.2 Robustness for interaction effect of hurricane and CSR using PSM analysis*

In this section, I conduct several tests to examine the robustness concerning my discovery above that interaction between hurricane and CSR is positively associated with the stock performance of firms.

I first test the sensitivity of my results to other definitions of the CSR measure based on KLD data, by splitting CSR into two component *Strengths* and *Concerns*. The results are presented in Panel A of Table 5.7. As being shown in columns (1) and (2), there is a negative relation between the Hurricane and CSR Strengths interaction term on stock return, while interaction of hurricane with CSR concerns is positively correlated to stock return. Specifically, one-standard deviation of the interaction leads to a 1.6% point decrease in the raw stock return and a 1.2% point decline in the abnormal return. In term of significance, the results of *Hurricane x CSR Concerns* are strongly significant at the 1% level. Similarly, I find a positive effect of *Strengths* and a negative impact of *Concerns* with respect to stock liquidity in columns (3) and (4).

Furthermore, according to Lins et al. (2017), I continue to test which categories of CSR are more valuable in affecting hurricane-stock return and stock liquidity. CSR is split into two components, those that communicate mostly to internal stakeholders (Employee Relations and Diversity), and those that speak primarily to external stakeholders (Community, Human Rights, and Environment). The estimated results are shown in Panel B. Specifically, I find no impact of internal CSR on stock performance as the coefficients of the interaction term are insignificant except for the case of raw return with significance at the 10% level. Meanwhile, external components of CSR are more important concerning the positive effect of CSR engagement in stock performance as the estimated coefficients are positive and strongly significant for all columns

Mullen (1997) argues that CSR program will need at least three to five years to generate the positive effect on firms. Thus, I next investigate whether my findings are because of short-term or long-term CSR. According to Shiu and Yang (2017), I define short-term and long-term CSR as follows:

$$SCSR_{i,t} = \frac{CSR_{i,t}}{ICSR_{i,t}} \, x \, 100 \tag{5.8}$$

$$LCSR_{i,t} = \frac{1}{2} SCSR_{i,t-1} + \frac{1}{4} SCSR_{i,t-2} + \frac{1}{8} SCSR_{i,t-3} \tag{5.9}$$

where $SCSR_{i,t}$ is short-term CSR of firm i in year t, $CSR_{i,t}$ is raw CSR score of firm i in year t, $ICSR_{i,t}$ denotes the industry average raw CSR score for all firms in the industry of firm i. $LCSR_{i,t}$ represents long-term CSR of firm i in year t. I then repeat the same regression as above and report the results in Panel C of Table 5.7. In terms of stock returns, the coefficients indicate that both short-term and long-term CSR contribute to the positive effect of CSR on hurricane-stock return relation, but the impact of long-term CSR is stronger with significance at the 1% level. Meanwhile, this chapter does not observe the contribution of short-term CSR on stock liquidity as the estimates when using trading volume and the RtoV and RtoTRF ratios as liquidity measures are insignificant. However, when using the RtoTR ratio to measure stock liquidity, I find a positive coefficient of *Hurricane*Short-term Strategy* but it is only significant at the 10% level. This result is consistent with the finding of Shiu and Yang (2017), that CSR engagement on a long-term basis provides insurance-like effect on firms' stock price in the face of a negative event.

**Table 5.7: The Effect of CSR on the Hurricane-Stock Performance Relationship-Robustness**

This table presents the regression results for the effect of CSR on the hurricane-stock performance relationship. Columns (1) and (2) present the results for stock return and columns (3) to (6) for stock liquidity. Stock return and liquidity data are obtained from CRSP. *Raw Return* is the monthly raw return. *Abnormal Return* is the monthly market-model adjusted return. *Trading Volume* is the raw trading volume in US dollars. *RtoV* is the Amihud illiquidity multiplied by minus one, where Amihud illiquidity is computed as the monthly average of the daily ratio of absolute value of stock return divided by dollar trading volume multiplied by one million. *RtoTR* and *RtoTRF* is the return to turnover ratio and price impact adjusted free float factor multiplied by minus one, respectively. *Hurricane* is a dummy variable equal to one for firms that located in a hurricane-struck county over the period after the hurricane, and zero for the treatment firms before the hurricane and for all the control firms. The characteristics based on market data (momentum, size, market-to-book, factor loadings) are updated monthly. Factor loadings are re-estimated each month based on the previous 60 months' data. The Appendix gives the definitions of all the variables. All regressions include year and industry fixed effects. Industry effects are based on two-digit SIC codes. Standard errors reported in parentheses are based on standard errors adjusted for heteroskedasticity and clustering at the firm level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

**Panel A: CSR Strengths and Concerns**

| | **Stock Return** | | **Stock Liquidity** | | | |
|---|---|---|---|---|---|---|
| | **Raw Return** | **Abnormal Return** | **Trading Volume** | **RtoV** | **RtoTR** | **RtoTRF** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Hurricane*CSR Strengths | 0.006** | 0.005* | 0.035** | 0.069*** | 0.019** | 0.013* |
| | (0.003) | (0.002) | (0.016) | (0.026) | (0.009) | (0.006) |
| Hurricane*CSR Concerns | -0.016*** | -0.012** | -0.017* | -0.128*** | -0.051* | -0.028** |
| | (0.006) | (0.005) | (0.009) | (0.044) | (0.028) | (0.014) |
| Firm characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Four-factor loadings | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Obs. | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 |
| Adjusted $R^2$ | 0.011 | 0.007 | 0.545 | 0.091 | 0.342 | 0.194 |

**Panel B: Internal and External Stakeholder CSR**

| | **Stock Return** | | **Stock Liquidity** | | | |
|---|---|---|---|---|---|---|
| | **Raw Return** | **Abnormal Return** | **Trading Volume** | **RtoV** | **RtoTR** | **RtoTRF** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Hurricane*Internal CSR | 0.008* | 0.005 | 0.011 | 0.044 | -0.029 | 0.005 |
| | (0.004) | (0.004) | (0.010) | (0.037) | (0.044) | (0.027) |
| Hurricane*External CSR | 0.016*** | 0.013*** | 0.093*** | 0.154*** | 0.069*** | 0.020** |
| | (0.006) | (0.005) | (0.023) | (0.041) | (0.026) | (0.010) |
| Firm characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Four-factor loadings | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Obs. | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 |
| Adjusted $R^2$ | 0.011 | 0.007 | 0.484 | 0.088 | 0.484 | 0.088 |

**Panel C: Long-Term and Short-Term Strategy**

| | **Stock Return** | | **Stock Liquidity** | | | |
|---|---|---|---|---|---|---|
| | **Raw Return** | **Abnormal Return** | **Trading Volume** | **RtoV** | **RtoTR** | **RtoTRF** |
| | **(1)** | **(2)** | **(3)** | **(4)** | **(5)** | **(6)** |
| Hurricane*Long-Term Strategy | 0.012*** | 0.010*** | 0.025*** | 0.098*** | 0.097** | 0.043* |
| | (0.004) | (0.004) | (0.004) | (0.026) | (0.041) | (0.023) |
| Hurricane*Short-Term Strategy | 0.010** | 0.008* | 0.004 | 0.065 | 0.017* | 0.035 |
| | (0.005) | (0.005) | (0.010) | (0.093) | (0.009) | (0.026) |
| Firm characteristics | Yes | Yes | Yes | Yes | Yes | Yes |
| Four-factor loadings | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Obs. | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 | 35,909 |
| Adjusted $R^2$ | 0.011 | 0.007 | 0.477 | 0.089 | 0.184 | 0.162 |

### 5.5 Conclusion

This chapter provides empirical evidence that engaging in CSR activities is beneficial to firms when facing the occurrence of negative shocks as hurricane strikes. In particular, I find that firms with high CSR scores outperform companies with low CSR scores after controlling for several firms' characteristics and risk factors. This chapter first shows that CSR provides insurance-like effect on the abnormal stock return when the firms are affected by the hurricane. This effect persists when I use alternative CSR measures and control for corporate governance. However, I do not observe the positive impact of CSR on stock return before the occurrence of hurricane strikes.

I next provide evidence that CSR engagement is positively correlated to hurricane-stock return and stock liquidity of firms. Using propensity score matching analysis, this chapter shows that the coefficients of hurricane and CSR interaction are positive and significant for both stock return and stock liquidity. I also report that these effects are because of both CSR strengths and concern components. Moreover, external categories including Community, Human Rights, and Environment mainly contribute to this positive impact. Long-term investment in CSR provides insurance-like effects of CSR on firms' stock performance.

Overall, the findings of this chapter have important implications for corporates, researchers and investors. First, given my results, it is expected that engaging in CSR activities for a long time can be an insurance policy of firms, which pays off when there is an occurrence of negative shocks such as hurricane strikes. Thus, policy makers of firms should consider carefully the effect of CSR before making decisions. Besides, the positive relationship between CSR and stock return has practical implications for managers seeking to generate value from CSR engagement. In addition, this chapter also reveals that CSR can be an important determinant of stock performance. This has real implications for researchers, who are interested in stock return and asset pricing fields to control for CSR effects. Finally, in terms of investors, my results have important implications for decision–making before investing in a specific stock. Further research could focus on the insurance-like effects of CSR on stock performance, employing data in different stock markets or using another shock other than hurricanes as a comparison.

**Appendix. Variable definitions.** This appendix provides detailed definitions of the variable used in this chapter. Data are from COMPUSTAT, unless otherwise noted.

| Variable | Definition |
|---|---|
| Board Independence | Fraction of board consisting of outside directors in percentage. |
| Board Ownership | Fraction of outstanding shares owned by board members in percentage . |
| Board Size | Total number of members of the board of directors. |
| Book-to-market | Book value of equity divided by market value of equity. |
| CAR (-1,5) | Cumulative abnormal stock returns obtained over the window from 1 day before the hurricane strike date to 5 day after the hurricane strike date (Source: CRSP). |
| CAR (-1,10) | Cumulative abnormal stock returns obtained over the window from 1 day before the hurricane strike date to 10 day after the hurricane strike date (Source: CRSP). |
| CAR (-1,30) | Cumulative abnormal stock returns obtained over the window from 1 day before the hurricane strike date to 30 day after the hurricane strike date (Source: CRSP). |
| Cash holdings | Cash and marketable securities divided by assets. |
| CEO Duality | A dummy variable that is equal to one if a firm has CEO Duality, zero otherwise. |
| CSR | The total net CSR measure, is computed as the sum of the net CSR indices for the five categories (Source: KLD) |
| CSR Concerns | Sum of yearly adjusted CSR activities, diversity, employee relations, environmental record, human rights, and community concern scores from KLD. I construct adjusted concern scores by scaling the raw concern scores of each category by the number of concern indicators for that category and year. |
| CSR Strengths | Sum of yearly adjusted CSR activities, diversity, employee relations, environmental record, human rights, and community strength scores from KLD. I construct adjusted strength scores by scaling the raw strength scores of each category by the number of strength indicators for that category and year. (Source: KLD) |
| Dividend | Annual cash dividends on ordinary stock |
| Firm size | The natural logarithm of total assets |
| Hurricane | A dummy variable equal to one for firms that located in a hurricane-struck county over the period after the hurricane, and zero for the treatment firms before the hurricane (Source: SHELDUS) |
| Leverage | Ratio of total liabilities to total assets. |

| | |
|---|---|
| Long term debt | Long-term debt divided by assets. |
| Negative B/M | A dummy variable set to one when the book-to-market ratio is negative and zero otherwise. |
| Profitability | Ratio of operating income divided by assets. |
| R&D | Ratio of research and development expenditure to total assets. |
| Raw CSR | The net CSR score computed by subtracting the concerns scores for all the five dimensions from the strength scores (Source: KLD) |
| ROA | Ratio of earnings before extraordinary items to total assets. |
| Short term debt | Ratio of debt in current liabilities divided by assets. |
| Internal CSR | CSR score which combines the measures for diversity and employee relations (Source: KLD) |
| External CSR | CSR score which combines the measures for community, environment, and human rights (Source: KLD) |

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# CHAPTER 6: CONCLUSION

## 6.1 Summary and Implication

The principal aim of this thesis is to provide empirical evidence about stock liquidity and stock return, motivated by the literature review in Chapter 2. In particular, the thesis investigates i) the relationship between stock liquidity and asset pricing using a new proposed price impact ratio, ii) the joint effect of advertising and market product competition on stock return, and iii) the relationship between corporate social responsibility and stock performance following a hurricane.

Chapter 3 provides new evidence of the effect of stock liquidity on asset pricing. Specifically, we investigate this association using the free float adjusted price impact ratio, recently proposed by Karim et al. (2016). This ratio is an alternative to the widely used liquidity Amihud (2002) illiquidity ratio and calculated by replacing trading volume in the denominator component of the Amihud ratio, by adjusted turnover ratio controlling for the public free float factor. Based on a sample of public firms in the US in the period from 1996-2017, this chapter has shown that the new ratio has additional appealing features compared to the Amihud ratio, as it captures the real supply of stocks on the market. Interestingly, stock liquidity is positively related to stock returns using the new free float ratio and return to turnover ratio, whereas the opposite is the case for the Amihud ratio.

The implication of chapter 3 is important for both researchers and practitioners. Specifically, this chapter employs a new price impact ratio as a liquidity measure, which is a more comprehensive alternative to the Amihud ratio. It provides researchers and practitioners with a more accurate approximation of stock liquidity. As a result, this measure provides investors with more confidence in investing and improves the academic research quality. In addition, the positive relationship between the new price impact ratio and stock return indicates that liquidity is significantly related to the trading frequency of investors.

Chapter 4 offers new evidence on the effect of advertising and product market competition on stock returns. Using a sample of all public firms in the US market from 1977 to 2018, this chapter reports the negative correlation between advertising and stock return and the positive effect of product market competition and stock return. Interestingly, this chapter shows that the negative impact of advertising on stock return is stronger for firms in high competitive industries. Meanwhile, firms with low advertising intensity exhibit a stronger and positive relation between competition level and stock return.

The results of this chapter have critical implications for both academics and practitioners. For example, when firms decide to invest in an advertising campaign, they should be cautious as my results show that there is an adverse effect of advertising on stock returns, especially for firms in competitive industries. Moreover, this chapter also suggests that firms in competitive markets earn higher expected stock returns than firms in concentrated industries, especially among low advertising intensity groups.

Chapter 5 investigates the relationship between corporate social responsibility (CSR) and stock performance under the occurrence of hurricane strikes. Using the difference in difference analysis I find that stocks of firms with high CSR score outperform firms with low CSR even after controlling for several firm characteristics. This chapter also confirms the insurance-like effect of CSR on abnormal stock returns for hurricane-affected firms. Moreover, using propensity score matching analysis, this chapter shows that firms engaging in CSR activities have superior stock returns and stock liquidity following a hurricane event, compared to other firms without CSR. Both CSR strengths and concerns contribute to these effects. However, this effect is seen only through the face of hurricane strikes.

These findings offer valuable insights for academics, policymakers and investors. In particular, this chapter suggests that investing in CSR can be an insurance policy of firms for a long time, especially when there is an exogenous shock such as a hurricane. This chapter also shows that CSR is an important determinant of stock return and stock liquidity. As a result, it is important for academics and investors when considering stock performance of firms.

In summary, my thesis adds contribution on the literature, specifically in the liquidity and asset pricing field, and has important implications for both academics and practitioners. First, the thesis provides new evidence about the relation of stock liquidity and stock return using a new proposed price impact ratio. This new liquidity measure is shown to more accurate and comprehensive than existing price impact ratios. This evidence allows both researchers and investors to be more confident in choosing the suitable liquidity measure for their research and investments. It also boosts the quality of academic research as well as investor's decision about stock liquidity and stock return. Second, the empirical results about the relationship between advertising, product market competition and stock return in chapter 4; and between CSR and stock performance in chapter 5 suggest that these factors can be important determinants of stock return. Everyone, who has an interest in stock returns and asset pricing should benefit from my thesis.

### 6.2 Limitations and Opportunities for Future Research

A few limitations to this analysis have been identified. First, as I cannot access the high frequency data of transactions, chapter 1 uses low frequency data (daily data). This data source may decline the accuracy of the empirical results about the relationship between stock liquidity and stock return. Second, the availability of hurricane data limits the number of hurricane observations available for the CSR study. Specifically, the sample period only covers the duration from 1992 to 2007. This may raise concerns about whether the finding of chapter 5 is driven by the sample period.

The importance of stock liquidity and stock return in the literature has been highlighted throughout this thesis. In addition to the empirical results and analysis of this thesis, several avenues for future research can be suggested. First, with regard to the free float adjusted price impact ratio, which is considered in chapter 3. Using the US stock data, chapter 3 shows that this new liquidity measure is superior to the other price impact ratios, including the Amihud ratio and the return to turnover ratio of Florackis et al. (2011) in capturing liquidity of stocks. Potential research can test this finding using different stock markets, such as developing markets as alternative market structures can lead to differences in liquidity characteristics.

Second, chapter 4 provides empirical evidence about the joint effect of advertising and product market competition on stock returns. It is valuable for further research to investigate possible reasons behind this relation.

Finally, following the positive effect of CSR on stock performance, it is interesting for further research to examine the possible sources of the positive impact, i.e., it happens only after an exogenous shock like a hurricane. Moreover, due to the availability of CSR data, the sample period ends in 2012. Extending the data would help to provide a more complete understanding of the effect of CSR.