Limits to information consumption in corporate finance and investment management

by

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Declarations

This thesis is submitted to the University of East Angelia in support of my application for the degree of Doctor of Philosophy in Finance. It has been composed by me and has not been accepted in substance for any degree and is not concurrently being submitted for any degree of award.

Jiaoshan Li

Abstract

This thesis aims to deepen our understanding of the role of information in finance by addressing several key research questions and providing novel insights and empirical evidence. The thesis comprises three main chapters, each focusing on distinct dimensions of information consumption and its implications for various financial phenomena.

Chapter 1 investigates the impact of time zone differences on M&A performance in financial markets. Drawing from a comprehensive dataset of 3,854 M&A transactions initiated by Chinese firms across 88 countries, the study examines the relationship between time zone differences and deal completion time. The findings reveal a significant association, indicating that larger time zone differences result in longer completion times. Specifically, a one-hour increase in time zone difference leads to an average delay of 5.7 days in completing the deal. The impact could be even more pronounced when dealing with larger time zone differences. Given that firms are more likely to use cash to settle the acquisition because managers may have better information about the deal (e.g., Louis, 2004), we find evidence that acquirers tend to use cash in M&As when the time zone difference is smaller. This evidence suggests that the time difference between acquirers and targets create information asymmetry, resulting in uncertainties for managers to use cash to complete the deal. Additionally, the study explores the relationship between time zone differences and cumulative abnormal returns around the takeover announcement date. The results demonstrate a negative association, highlighting the role of information asymmetry arising from time differences in influencing market reactions to M&A announcements. Overall, these findings contribute to our understanding of the challenges faced by firms engaged in cross-border M&A transactions.

Chapter 2 makes a valuable contribution to the field by examining how the incorporation of investor attention variables can enhance stock covariance forecasting. Investor attention serves as a vital proxy for information processing and dissemination within financial markets. By investigating the impact of investor attention on the forecasting ability of the covariance matrix, the chapter provides valuable insights into the role of information in guiding portfolio management decisions. Using the Google search volume index (GSVI) as a proxy for investor attention, the study investigates the impact of investor attention on the predictability of stock covariance. By applying multivariate models, including random walk estimation and the heterogeneous autoregressive model, the study demonstrates that the inclusion of investor attention variables significantly improves the accuracy of covariance forecasting. The results consistently support the hypothesis that investor attention plays a valuable role in enhancing stock covariance forecasting. These findings contribute to the existing literature by highlighting the importance of considering investor attention as an influential factor in financial forecasting models.

Chapter 3 delves into the dynamics of household stock market participation and its implications for wealth distribution. Using comprehensive data from the Wealth and Assets Survey (WAS) in the UK, the study explores factors influencing household participation in the stock market, both directly and indirectly. The analysis uncovers that gender and income play significant roles in determining the probability of stock market participation. Furthermore, the study investigates the behavior of the wealth distribution and its components, shedding light on the effects of stock market participation on wealth disparities. Notably, the findings highlight that total participation has a larger effect on the overall wealth distribution. Moreover, indirect stock market participation exerts a slightly higher impact compared to direct participation across all five waves analyzed. These insights deepen our understanding of the complexities of household investment decisions and their implications for wealth inequality.

These chapters collectively contribute to our knowledge of how information influences decision-making in finance. The findings highlight the impact of time zone differences on M&A performance, the significance of investor attention in stock covariance forecasting, and the effects of stock market participation on wealth distribution dynamics. These contributions enhance our understanding of the intricate relationship between information, decision-making, and financial outcomes.

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Last but not least. To this beautiful world.

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Introduction

How information has been taken into account is one of the most fundamental questions in finance. It has long been accepted that the relevance of information matters in the explaining risk premia in the cross-section of stock returns (Ben-Rephael et al., 2021; Ho and Hung, 2009; Hua, Xiao and Zhou, 2021), in the determination of a firm's cost of capital (Armstrong et al., 2011; Easley and O'hara, 2004; Lambert, Leuz and Verrecchia, 2012), in explaining the household behavior, such as the saving behavior (Dolls, et al, 2018) and household portfolio choice (e.g. Bluethgen, et al., 2008; Van Nieuwerburgh and Veldkamp, 2009; Van Nieuwerburgh, and Veldkamp, 2010), also in the firm decision making (see Varis, M. and Littunen, H., 2010; Bloom, et al., 2008).

This thesis illuminates the crucial role of information in the field of finance. Comprising of three main chapters, the thesis delves into various aspects concerning the limitations of information consumption in corporate finance and investment management. By exploring these issues, this research contributes to our understanding of the challenges and complexities associated with information in financial decision-making processes. Chapter 1 contribute to the literature by examining the influence of time zone differences as a proxy for information asymmetry in mergers and acquisitions. This investigation explores how differences in time zones can affect the consumption of information and, subsequently, the outcomes of M&A deals. By focusing on time zone differences, the chapter provides a unique perspective on information asymmetry in cross-border deals, contributing to our understanding of the complexities surrounding M&A transactions. Chapter 2 focuses on the role of investor attention in improving the forecasting of the covariance matrix. This study is of great significance, highlighting the importance of considering investor attention as a valuable input in financial forecasting models. By examining how investor attention, captured through the Google search volume index, the findings offer valuable implications for portfolio managers, risk analysts, and investment professionals who rely on accurate covariance forecasts for effective risk management and asset allocation strategies, thereby bridging the gap between theoretical models and empirical practices in portfolio management. In Chapter 3, the investigation delves into the impact of household characteristics and behavioral biases on information consumption related to stock market participation. Financial theory indicates that information frictions, such as the information and transaction costs, in the market could account for the limited stock market participation rates. This research also examines how these factors influence investors' decision-making processes and, in turn, impact the wealth distribution. By exploring the nuanced relationship between investor behavior and wealth inequality, the chapter contribute to a better understanding of the determinants of stock market participation and provide insights into the dynamics of wealth inequality. This investigation offers valuable implications for policymakers and practitioners seeking to promote more inclusive and equitable financial systems.

Chapter 1 investigates the effect of time zone on the Mergers and Acquisitions (M&A) activities. When the information asymmetry is severer, investors may face uncertainties concerning the firms' cash flow and the synergy gain (Hackbarth and Morellec, 2008). Furthermore, Dionne et al. (2015) and Bick et al. (2017) show that shareholders are very likely to react negatively to such deals that are characterized with greater uncertainties, which will result in lower announcement returns and acquisition premiums.

Although, a large body of studies focus on how spatial distance affects Merger and Acquisition activities, to name a few, Ragozzino (2009) and Mitchell (2016) reveal that distance negatively affects acquisition premiums, surprisingly, little is known about the relationship between time zone difference, as a proxy of information asymmetry, and M&As. It can be served as a proxy of information asymmetry because it creates temporal disparities, hinders real-time communication, leads to delayed responses, etc. These factors contribute to information asymmetry between market participants operating in different time zones. Stein and Daude (2007) and Hummels and Schaur (2013) document that time zone affects a country's investment and trade activities, respectively. Thus, time is an important factor for firms' investments across different counties.

The completion time of M&A deals is an important factor in understanding the efficiency and effectiveness of the deal-making process. The longer it takes to complete a deal, the higher the transaction costs and the greater the resource allocation required. Understanding how time zone differences influence the duration of deal completion can provide insights into the challenges faced by parties involved in cross-border transactions. For instance, if there is a substantial time gap between parties, it may lead to delays in communication, decision-making, and coordination, potentially prolonging the overall deal completion time. We have the first research question: 1) how does the time zone difference affect deal completion time? Furthermore, the information asymmetry can influence the acquisition process and potentially impact the abnormal return associated with the announcement of the deal. Investors may react differently to acquisition announcements. Understanding how time zone difference influences investor behavior can help market participants, regulators, and researchers better understand and predict market reactions to M&A events. Therefore, the second research question would be: 2) Does time zone difference affect the acquisition premium? Thirdly, exploring the acquirer's preference to settle the deal based on the time difference with the target firm is significant as it examines the influence of time zone differences on deal settlement strategies. Parties involved in M&A transactions may have varying preferences and priorities when it comes to finalizing the deal. If the acquirer's preference is influenced by the time difference, it suggests that they consider factors such as communication efficiency, decision-making processes, and coordination challenges associated with time zone disparities. Hence, we introduce the third research question: 3) Is the acquirer's preference to settle the deal driven by the time difference with the target firm? To address these research questions, we adopt 3,854 both the private and public cross-border Mergers and Acquisitions initiated by Chinese firms in 88 countries. The data we used spans from 01/01/1997 to 31/12/2020 from Bureau van Dijk's Zephyr databases.

We find evidence that a larger Time Zone Difference between acquirers (e.g., in China) and targets leads to a longer time to completion. One hour increase in the time difference results in 5.7 days, on average, to complete the deal. Furthermore, we provide evidence on the effect of time zone on deal announcement returns. We also find evidence that acquirers tend to use cash in M&As when the Time Zone Difference is larger. Our results are robust to the inclusion of various controls, such as deal and firm characteristics. Overall, our results suggest that Time Zone Difference across countries increases information asymmetry, creating difficulties for firms to conduct M&As overseas. It is the fact that around one third of the targets in Chinese cross-border merger and acquisition transaction were from Hong Kong and United States from the whole data observations. To ensure that our results are not driven by transactions in these two areas, we also perform the robustness check by excluding the transactions in these two areas. Our robustness check results confirm that our evidence is qualitatively unchanged, showing the Time Zone Difference significantly and negatively affect the cross-border merger and acquisition transactions.

Chapter 2 aims to contribute to the financial literature by exploring the relationship between investor attention and covariance forecasting, shedding light on the predictive power of investor attention in improving the accuracy of covariance forecasting. Investor attention serves as a crucial proxy for information processing and dissemination within financial markets.

By examining how investor attention impacts the forecasting ability of the covariance matrix, the chapter provides valuable insights into the role of information in guiding portfolio management decisions. The chapter also emphasizes the value of considering investor attention as an input for more accurate portfolio risk assessment, enabling more effective risk management and asset allocation strategies. Investor attention has been measured by various indicators, including the Google search volume index (GSVI, hereafter). Google search volume can capture retail investors attention more directly and timely (Da et al., 2011). GSVI, to some extent, can be used as a proxy of the information demand (e.g., see Vlastakis and Markellos, 2012; Chronopoulos, Papadimitriou, and Vlastakis, 2015).

This research aims to assess the investor attention by using Google search volume index in determining its effect on stock covariance forecasting, considering whether investor behavior can empirically enhance the predictability of covariance matrix forecasting in stock market. The empirical application is based on five main European stock markets, i.e., CAC 40, AEX, DAX, FTSE 100, and SMI. Our estimation sample ranges from 01 Jan, 2000 to 19 Apr, 2016. We used two methodologies, 1) the Random walk estimation (RWE), and 2) the Multivariate Heterogeneous Autoregressive model (VHAR) for our estimation purpose. We use both methods in our in-sample estimation and also the out-of-sample forecasting. Evidence from Euclidean distance, the Frobenius distance and the multivariate quasi-likelihood loss function suggest that the Multivariate Heterogeneous Autoregressive model outperform the Random walk estimation. The Our results, comparing the results with and without google search volume index, find that the GSVI does contribute and improve the covariance matrix prediction for both the crisis period and non-crisis period.

In Chapter 3, we investigate the drivers of the stock market participation and further to see how the household stock market participation affect the wealth distribution in the UK. These research questions motivate this chapter. The household stock market participation is a result of a comprehensive decision-making process, and it could be driven by different factors. In this study, we look at the characteristics of the household by using the information of the reference person in the household, namely the age, education, gender, employment, socio-economic status, and income. We use the Wealth and Assets Survey (WAS) data across five waves, from July 2006 to July 2016. The empirical results, applying the Ordinary least squares, logit and probit models, indicate that the female tends to have less participated in the stock market, and those households who have education qualifications tend to have more likelihood to participate. Moreover, the employment households are likely to participate into the stock market. Furthermore, we can see the higher income increase the participation in the stock market, either directly or indirectly.

We further show how the household stock market participation affect the wealth distribution in the UK. Theoretically, the wealth distribution can be also affected by several aspects. When looking at the impact of the stock market participation on the wealth distribution, our estimation results from the quantile regression suggest that the impact is much higher in the lower quantile rather than in the higher quantile. This result is consistent across the waves and the effect is larger from the total participation. In particular, the effects of indirect stock market participation are greater than those of direct participation. Our results have important policy implications: any intervention in the stock market participation will affect the left tail more than the right tail. In other words, this well affect more in the households with relative lower wealth. From these results, we can see the stock market participation could be one of the factors in explaining the wealth inequality in the UK.

Chapter 1. Time zone as a barrier: Evidence from Cross-border Merger and Acquisition in China

1. Introduction

Information asymmetry plays an important role in corporate mergers and acquisitions (M&As) (e.g., Officer et al. 2009; Cuypers et al. 2017). A considerable literature investigates the role of geographical distance in forming asymmetric information environment in M&As, which results in a lower acquisition premium and a longer time to completion (Bick et al. 2017), reduced probability of successful deals (Chakrabarti and Mitchell, 2016), and biased target firm selection (Chakrabarti and Mitchell, 2013). However, some studies argue that, similar to spatial distance, the difference across various time zones also serve as a source of information disparity, which impedes the economic and corporate activities, such as foreign direct investments and equity transaction flows (e.g., Portes and Rey, 2005; Stein and Daude, 2007). Surprisingly, little is known about the relationship between time difference and M&As. Thus, this study aims to fill the gap in the literature by exploring how time zone affects M&As performance in financial markets.

The time difference is deemed as a source of increased communication costs for the business world. For instance, if a company located in China sends an e-mail at 10 am to another company located in the UK, the latter will need to wait for at least six hours to be able to process the e-mail (e.g., from 9 am in the UK time). This is because of the Time Zone Difference, where China is in GMT +8 while the UK is in GMT +1. Thus, different time zones cause barriers for companies to coordinate employees, thereby diminishing productivity (Gong, 2020). Time zone differences capture the temporal availability of information and communication between firms in different regions. In the case of Beijing with Seoul, despite a relatively short geographic distance, there is a time zone difference of one hour. This time zone difference affects the real-time information flow. This temporal asymmetry can lead to challenges in information dissemination and decision-making. While in the case of Beijing with Hong Kong, even with longer distance, no time zone difference allows for relatively easier coordination and real-time communication due to overlapping business hours. During the process of M&As, acquirers must obtain enough knowledge about the targets, especially in cross-border transactions. However, since distance hampers the flow of information in M&As (e.g., Chakrabarti and Mitchell, 2013), we explore the following research questions: how does the Time Zone Difference affect deal completion time? Does Time Zone Difference affect the acquisition premium? Is the acquirer's preference to settle the deal driven by the time difference with the target firm?

In this study, we conjecture that, regardless of geographical distance, acquirers and targets share more overlapped working hours (e.g., smaller time difference across different time zones) enjoy a local information advantage, which reduces time to complete the deal, and vice versa. Drawing from 3,854 private and public M&As initiated by Chinese firms in 88 countries, we find evidence that a larger Time Zone Difference between acquirers (e.g., in China) and targets leads to a longer time to completion. One hour increase in the time difference results in 5.7 days, on average, to complete the deal. However, the impact becomes even more substantial when dealing with larger time zone differences, such as parties in New York and China mainland. Our results are robust to the inclusion of various controls, such as deal and firm characteristics.

Furthermore, we also examine the effect of time zone on deal announcement returns. We document a negative relationship between time difference and cumulative abnormal returns around the takeover announcement date. Given that firms are more likely to use cash to settle the acquisition because managers may have better information about the deal (e.g., Louis, 2004), we find evidence that acquirers tend to use cash in M&As when the Time Zone Difference is larger. This evidence suggests that the time difference between acquirers and targets create information asymmetry, resulting in uncertainties for managers to use cash to complete the deal. Overall, our results suggest that Time Zone Difference across countries increases information asymmetry, creating difficulties for firms to conduct M&As overseas.

This study makes significant contributions in several directions. First of all, previous studies suggest that Time Zone Difference increases information asymmetry, which negatively affects B2B online business (Zaheer and Zaheer, 2001), equity flows (Portes and Rey, 2005), and foreign direct investments (Stein and Daude, 2007). Thus, we add to this stream of emerging literature by revealing that the time difference deteriorates the performance of M&As.

Second, Gulamhussen et al. (2016) investigate the relationship between different time zones and M&As in commercial banking. We update their study using a comprehensive dataset from all industries. Given that financial firms usually expose to restrictive regulations, our evidence suggests that the adverse effect stemmed from time difference on M&As does not exclusive to the banking sector. Gong (2020) documents that Time Zone Difference affects within-country M&A deals negatively (e.g., the U.S.). Our study differentiates from his study in two ways. First, since cross-border transactions face more diverse challenges, such as economic and political uncertainties, we extend his study by utilizing M&As deals from 98 countries. Secondly, our study also considers private deals, which share distinct characteristics with public deals. Thus, our study provides robust evidence that Time Zone Difference negatively affects M&As outcomes by increasing time to completion and decease deal announcement returns.

The rest of the chapter is organized as follows. Section 2 provides the literature review. We develop the hypotheses in Section 3. Section 4 describes sample selection. Section 5 present empirical results. Finally, Section 6 concludes the chapter.

2. Literature review

2.1 Geographical distance and M&As

A large body of studies focuses on how spatial distance affects M&As. Chakrabarti and Mitchell (2016) find that geographic distance reduces the probability of successful deal completion. They indicate that distance limits information acquisition and managers' interaction with target firms. Bick et al. (2017) reveal that distance negatively affects acquisition premiums and time to completion, conditional on small-sized firms. This finding suggests that asymmetric information matters for acquiring small firms. In this regard, acquirers prefer to takeover geographically proximate targets (Schildt and Laamanen, 2006). Ragozzino and Reuer (2011) document that various IPO firms' characteristics (e.g., having reputable underwriters) serve as positive signals to attract distant acquirers. Nevertheless, distance is likely to be a factor that affects acquirers' ability to evaluate and control the remote targets (Malhotra and Gaur, 2014). Ragozzino (2009) argues that geographical distance affects firms' corporate governance decisions in acquisitions. Specifically, he shows that firms prefer to take full ownership from distant targets and shared ownership for proximate deals.

Although geographical space hampers the process and outcome of M&As, some studies find that firms' prior experience can mitigate negative effects caused by distance. For instance, Chakrabarti and Mitchell (2013) argue that acquirers are more likely to select distant targets if they have obtained related experience in that area. Thus, geographical distance plays an important role in corporate decision making and investment outcomes (e.g., Sorenson and Stuart, 2001; Golledge, 2002).

2.2 Information asymmetry in M&As

Previous studies suggest that a higher level of information disparity negatively affects deal outcomes and wealth developed by both acquirers and targets (e.g., Hansen, 1987; Chemmanur et al., 2009; Eckbo et al., 1990; Officer et al., 2009). Hansen (1987) argues that the asymmetric information affects the means for acquires to complete the deal. He predicts that acquirers prefer to use stock to finance the deal when their stock valuation is overestimated. Luypaert and Van Caneghem (2017) investigate the relationship between information asymmetry and payment preference for both acquirers and bidders. They reveal that stock settlement is used if higher uncertainty is from acquirers, and cash settlement is chosen if information disparity is more pronounced in targets. Thus, their study complements the prediction made by Hansen (1987). In a similar vein, Reuer et al. (2004) find that bidders use stocks to acquire targets in high-tech and service industries, as firms in those industries often involve a higher level of valuation uncertainty. However, stock financed deals negatively affect announcement returns than cash financed deals (Travlos, 1987; Faccio and Masulis, 2005), which is likely to be caused by the adverse selection about the uncertainty of the bidder's firm value (Korajczyk et al., 1991).

Another aspect that how asymmetric information affects M&As is about resulting wealth. When the information asymmetry is severer in targets, investors face uncertainties relating to the firms' cash flow and the synergy gain (Hackbarth and Morellec, 2008). Thus, shareholders are likely to react negatively to such deals that are characterized with greater uncertainties, resulting in lower announcement returns and acquisition premiums (e.g., Dionne et al., 2015; Bick et al., 2017). Moreover, acquirers tend to conceal acquisitions gains by offering target shareholders with cash in the presence of higher information asymmetry (e.g., Luypaert and Van Caneghem, 2017). Therefore, Information asymmetry plays a significant role in the process of corporate M&As.

2.3 Time zone effect

Previous studies explore how Time Zone Difference as the cost of communication affects economic and corporate activities. Zaheer and Zaheer (2001) argue that time zone affects global B2B online businesses by influencing customers' choice. Portes and Rey (2005) imply that investors experience difficulties in placing trades across counties with distinct Time Zone Difference. Thus, they find that overlapped trading hours increase equity transaction flow. Stein and Daude (2007) document that foreign direct investments are negatively associated with time zones. They further find that this relationship remains even if information technology is improved. Similarly, Hummels and Schaur (2013) document that time lags in transit affect a country's exporting activities. Thus, time is an important factor for firms doing businesses across different counties.

With regard to M&As, Gulamhussen et al. (2016) suggest that time differences raise barriers in communication between acquirers and targets, which negatively affects deal success and value in commercial banking. The study of Gong (2020) shows evidence that time zone hinders employee coordination in M&As setting, thereby reducing announcement returns. Nevertheless, both studies focus on the within-country effect of time difference on M&As. It is unclear how time zone affects cross-border M&As, as firms doing businesses in other counties face greater challenges.

2.4 M&As in China

Firms in China are entering into new markets or territories by mergers and acquisitions transaction. Various factors affecting the mergers and acquisitions decision have been studied. Borthwick, Ali and Pan (2020) and Sha, Kang and Wang (2020) have examined the connection between economic policy uncertainty and mergers and acquisitions in China. However, they find different effects of economic policy uncertainty. The former study shows that the economic policy uncertainty has the similar effect in both US and China, while the latter one states that Chinese companies are more likely to take M&As during high economic policy uncertainty time. Closer to our paper, Dong, et al. (2019) explores the effects of economic, cultural and institutional distances in affecting the M&As by Chinese firms. Other factors have also been examined in China. For example, Xiao (2020) looks at the anchoring effect in the M&A transaction; Liu, Wu and Guo (2021) provide an empirical investigation whether governmental governance of host countries has impact on the merger and acquisition performance.

Yet, we still have little idea whether the effects of Time Zone Difference on cross-border M&A completion and the performance. To fill this gap, we investigate its effect on different dimensions of the M&As, including the time to completion and cumulative abnormal returns.

3. Hypotheses Development

Time zone difference has gained the increasing attention in the area of financial geographic and financial investment. In line with the previous literature, we will test the main hypothesis that the time zone would have negative impact on the M&A transaction cases in this study by following research questions below:

1) Does the time zone difference have a positive or negative association with the successful implementation time of M&A deals?

2) Does time zone difference impact on the acquisition premium?

3) How does the time zone difference affect methods of payment in the M&A transactions?

4. Data and Methodology

4.1 Data

For our empirical analyses, we draw from Bureau van Dijk's Zephyr databases due to the fact that it provides much clearer information about the method of payment. We focus on the cross-border deals with acquirer from China and limit the deals with status as completed and have our sample from 01/01/1997 to 31/12/2020, the database records 7,097 cross-border M&A deals by Chinese firms. The deals involve 88 target economies.

To calculate the time zone between the two firms, we use the time zones of the headquarters of each. While most countries have a single time zone, we account for multiple time zones in countries with such characteristics, like the United States. Our measure to some extent has its potential weakness. For example, geographically, China spans five time zones. However, all provinces are in the same time zone.

Dependent variable

As we noted previously and consistent with previous research on M&As (Walter, Yawson and Yeung, 2008; Luypaert and De Maeseneire, 2015), we interest in how the Time Zone Difference as an information asymmetry proxy affect the M&As performance. As one of our main variables of interest, the Time Zone Difference, will have affect the time to completion. We expect that the larger Time Zone Difference measure will delay the deal completion and thus increase the time to deal completion.

This study also follows the literature (see Netter, Stegemoller and Wintoki, 2011; Asimakopoulos and Athanasoglou, 2013; Gong, 2020) by considering the cumulative abnormal returns during the event window of 3 days (-1, +1) and 5 days (-2, 2). The data on cross-border M&As from The Zephyr are merged with the trading data with daily stock price and returns data from the China Stock Market & Accounting Research Database (CSMAR). The acquirer cumulative abnormal returns (CAR) are calculated as a proxy of financial performance of Chinese acquirer and will be used to examine the reaction to the cross-border M&A announcements. We consider the event window of (-1, 1) and (-2, 2), i.e., cumulative abnormal returns (-1, 1) and cumulative abnormal returns (-2, 2), respectively.

The choice of payment method (e.g., Faccio and Masulis, 2005; Netter, Stegemoller and Wintoki, 2011) has been widely examined in the literature. This study will follow the literature to look at how the Time Zone Difference will affect the choice of payment method in the M&A transactions.

Control variables

We include an array of control variables, i.e., the deal-level controls, the firm-level controls and macro-level controls. To account for deal-level factors, as Schweizer, Walker and Zhang

(2019), Gao, Huang, and Yang (2019) and Li, Wang, Ren, and Zhao (2020) do, we include the deal value in million CNY, payment methods (Cash Payment dummy and Stock Payment dummy). The Deal type value measures how much percentage of the value of the target involved in the deal will be considered. The models will also include the dummy indicating whether the two firms are in the same industry, that is, same industry dummy. When two firms operate within the same industry, they are likely to have a shared knowledge base and understanding of industry-specific dynamics. This mutual familiarity and expertise can potentially lead to a lower level of information asymmetry between the acquirer and the target firm in same-industry acquisitions. By creating the same industry dummy variable, the study aims to investigate whether such acquisitions exhibit a different level of information asymmetry compared to transactions involving firms from different industries. We further use acquiror market capitalisation and acquiror industry to control for the impact of firm-level factors. As stated in Li, Wang, Ren, and Zhao (2020), the economic development of the host country also plays a great impact on the M&A deals. We obtain macro-level data for China. We considered the Economic Policy Uncertainty (see Baker, Bloom and Davis, 2016) and China GDP in trillion USD. The inclusion of Economic Policy Uncertainty as a control variable allows us to examine how policy uncertainty impacts the decision-making and investment behavior of Chinese firms involved in cross-border acquisitions. Elevated levels of EPU may prompt firms to exercise caution or delay their investment decisions due to concerns surrounding potential regulatory changes, political instability, or other uncertainties associated with economic policies. Additionally, incorporating the GDP enables capturing the macroeconomic environment and trends in economic growth within China. The size and trajectory of China's GDP play a role in shaping the appetite for cross-border M&A activities. A higher GDP signifies a robust economy and an increased availability of investment opportunities, motivating Chinese firms to participate in cross-border acquisitions.

Table 1: Distribution of Mergers and Acquisitions deals.

Panel A: Distribution of Mergers and Acquisitions deals by sectors (Fama--French 12 industry codes[1])		
Sector	Freq.	Percent
Consumer Nondurables	203	3.81
Consumer Durables	244	4.58
Manufacturing	650	12.19
Oil, Gas, and Coal Extraction and Products	110	2.06
Chemicals and Allied Products	169	3.17
Business Equipment	713	13.37
Telephone and Television Transmission	28	0.53
Utilities	64	1.20
Wholesale, Retail, and Some Services	199	3.73
Healthcare, Medical Equipment, and Drugs	200	3.75
Finance	2,041	38.29
Other	710	13.32
Total	5,331	100

Panel B: Distribution of Mergers and Acquisitions deals by year		
Year	Frequency	Percentage
1997	3	0.06
1999	1	0.02
2000	15	0.28
2001	15	0.28
2002	30	0.56
2003	79	1.48
2004	127	2.38
2005	97	1.82
2006	137	2.57
2007	156	2.93
2008	242	4.54
2009	237	4.45
2010	239	4.48
2011	262	4.91
2012	233	4.37
2013	219	4.11
2014	306	5.74
2015	533	10
2016	725	13.6
2017	641	12.02
2018	556	10.43
2019	296	5.55
2020	182	3.41
Total	5,331	100

[1] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12.

Panel C: Distribution of Mergers and Acquisitions deals by Payment method		
Payment method	Frequency	Percentage
Cash	3210	60.21384
Liabilities	115	2.157194
Shares	96	1.800788
Others	161	3.020071
Unknown	1,749	32.8081
Total	5,331	100

Table 1 below provides distribution of our sample deals. Panel A of this table reports the number of completed cross-border M&A transaction along with percentages across the Fama-French 12 sectors. We find that Chinese companies completed 5,331 deals between 1997-2020. Of these, 2,041 deals were completed in Finance sector, accounting for 38.29% of the total observations. However, only less than 100 deals in total in the Telephone and Television Transmission and Utilities sectors.

The Panel B shows the distribution of the number of overseas M&A transactions from the beginning of 1997 to the end of 2020. The larger numbers of the deals were taken place between 2015-2018 can be found in the table. We also see this is quite in line with the Schweizer, Walker and Zhang (2019), which studies the Cross-border acquisitions by Chinese privately-owned enterprises (POEs).

We next describe the choice of payment methods in the cross-border M&A transactions by Chinese firms. The Panel C shows the distribution of these deals according to the payment methods. Most of the transactions, we can see from the data, are made through the cash payment, 60% of the total deals.

Table 2: summary statistics.

Variable	Observations	Mean	Std. Dev.	Min	Max
Time Zone Difference	4,095	7.210012	4.295946	0	12
Days to Completion	5,331	330.9178	363.7281	-633	4589
cumulative abnormal returns (-1,1)	1,026	0.0013976	0.0302247	-0.2299429	0.0966877
cumulative abnormal returns (-2,2)	1,026	0.0038708	0.0394922	-0.3167215	0.1764521
Same industry dummy	5,331	0.1708873	0.3764457	0	1
Deal Value (in m CNY)	4,276	910.19	3463.76	0	49060
Deal type value	5,086	63.08474	38.96462	0	100
Cash Payment	5,331	.5933221	0.49	0	1
Stock Payment	5,331	.0180079	0.13	0	1
Acquiror market capitalisation	957	32427.84	131941.6	104.2371	1585320
China EPU	5,331	285.8169	222.9785	9.06671	970.83
China GDP (in trillion USD)	5,149	8.1	2.47	1.77	11.5

Table 2 below reports the summary statistics for the dependent and independent variables in our sample. As we can see from the table, Same industry dummy, Cash Payment, and Stock Payment are dummy variables. Same industry dummy =1 signifies the acquiring firm and the target firm are in the same industry. The payment method, Cash Payment, indicates that the deal is paid by cash method. While the stock payment show that the deal is paid through share method.

Table 3: Pearson correlation matrix.

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	Time Zone Difference	1										
2	Days to Completion	-0.0647*	1									
3	cumulative abnormal returns (-1,1)	-0.0428	-0.0048	1								
4	cumulative abnormal returns (-2,2)	-0.0378	0.0153	0.8028*	1							
5	Same industry dummy	-0.0367	0.022	0.6917*	0.7674*	1						
6	Cash payment dummy	-0.052	0.0141	0.6013*	0.6392*	0.8110*	1					
7	Deal Value	-0.0287	0.1726*	-0.0274	-0.0334	-0.0157	-0.0115	1				
8	Deal type value	-0.0932*	0.0485*	-0.0024	-0.0005	0.0013	0.0048	-0.0695*	1			
9	Acquiror market capitalisation	-0.0423*	0.2725*	-0.0016	-0.0179	-0.0045	-0.0032	-0.1589*	0.1302*	1		
10	China EPU	0.0890*	-0.0375	0.0275	0.0208	0.0079	0.0162	-0.0263	-0.003	0.0577*	1	
11	China GDP	-0.0492*	-0.0515*	0.0175	0.0138	0.0264	0.0283	0.0905*	-0.0247	0.0336*	0.4064*	1

We provide the Pearson correlation matrix in Table 3. Only the correlation between cumulative abnormal returns (-1,1) and cumulative abnormal returns (-2,2) and the correlation between Same industry dummy and the Cash payment dummy are greater than 0.8. But the correlation coefficients do not cause multicollinearity. We further check the multicollinearity issue; we confirm that the variance inflation factor scores are less than 10. For all the variables across models.

4.2 Methodology

As has been mentioned previously, we will carry out an in-depth analysis in the effect of time zone on various variables. To investigate how the time zone is associated with deal-specific days to completion, as in Asimakopoulos and Athanasoglou (2013) and Beltratti and Paladino (2013), we estimate the following model,

$$DtC_i = \alpha + \beta_1 \mathrm{TZD}_i + \beta_2 \mathrm{Deal\_Controls}_i + \beta_3 \mathrm{Firm\_Controls}_i + \beta_4 \mathrm{Macro\_Controls}_i + \delta_k + \sigma_t + \varepsilon_{i,t} \qquad (1)$$

Where DtC_i is the Days to Completion of deal i, δ_k are industry fixed effects, and σ_t are year fixed effects. The Time Zone Difference is the practice of interest. The model contains a set of control variables, e.g., deal controls, firm controls, and the macroeconomic controls.

$$CAR_i = \alpha + \beta_1 \mathrm{TZD}_{i_i} + \beta_2 \mathrm{Deal\_Controls}_i + \beta_3 \mathrm{Firm\_Controls}_i + \beta_4 \mathrm{Macro\_Controls}_i + \delta_k + \sigma_t + \varepsilon_{i,t} \qquad (2)$$

Where CAR_i is the cumulative abnormal returns of deal i, δ_k are industry fixed effects, and σ_t are year fixed effects. As in model (1), this model also considers the deal-, firm- and macroeconomic-level controls.

We estimate Logit model specifications following Rossi and Volpin (2004), Ismail (2011) and Huang, Officer, and Powell (2016),

$$PM(Cash = 1; Stock = 1)_i = \alpha + \beta_1 \mathrm{TZD}_i + \beta_2 \mathrm{Deal\_Controls}_i + \beta_3 \mathrm{Firm\_Controls}_i + \beta_4 \mathrm{Macro\_Controls}_i + \delta_k + \sigma_t + \varepsilon_{i,t} \quad (3)$$

Where $PM(Cash = 1; Stock = 1)_i$ is the Method of payment of deal i, δ_k are industry fixed effects, and σ_t are year fixed effects. The payment method is the dependent of interest: an indicator variable that takes a value of 1 if the payment method was transacted by cash (stock), and 0 otherwise.

5 Results

Days to Completion

The Table 4 presents estimates of equation (1) where the dependent variable is the days to completion with different specifications. In columns (1) and (2), the time zone difference and deal controls are considered as the independent variables. In columns (3) and (4), additional firm controls are added to account for other factors that may affect completion time. Columns (5) to (8) further extend the models by incorporating macro controls to capture broader economic factors.

Table 4: Time Zone Difference and Days to Completion.

VARIABLES	Days to Completion							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Zone Difference	5.702**	5.830***	16.47*	14.10	5.380**	5.660**	15.94*	13.95
	(2.245)	(2.223)	(9.313)	(8.796)	(2.313)	(2.313)	(9.329)	(9.302)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Firm Controls			√	√			√	√
Add Macro Controls					√	√	√	√
Year FEs		√		√		√		√
Industry FEs	√	√	√	√	√	√	√	√
Observations	3,854	3,854	588	588	3,709	3,709	554	554
R-squared	0.226	0.255	0.442	0.533	0.234	0.245	0.463	0.499

Note: This table shows the effect of Time zone on the days to deal completion. Days to Completion is defined as the number of days from the deal announcement to the deal completion. Time Zone Difference equals the number of differences in time zone between the target and the acquirer. The standard errors are reported in parentheses for each regression.

*** Indicates statistical significance at the 1% level.

** Indicates statistical significance at the 5% level.

* Indicates statistical significance at the 10% level.

In Table 4, we report the results. The results from Table 4 that the Time Zone Difference has significantly positive effect on the days to deal completion without controlling for the firm characteristics. The effects are consistent across model (1), (2), (5), and (6). One more Time Zone Difference between the two firms leads approximately 5.7 days to completion in Model (1). A 5.7-day delay resulting from a one-hour time zone difference can indeed be considered significant, especially if the typical completion time for M&A deals is relatively short. The impact could be even more pronounced when dealing with larger time zone differences. For example, if an M&A deal involves parties in New York and China mainland, a substantial time zone difference of 12 hours means that one party may receive crucial updates, access to local market news or market developments while the other is offline and the delayed response time can result in a significant delay of 68.4 days to complete the deal. This example underscores the notable consequences that arise from substantial time zone differences in the context of M&A transactions. When controlling for the firm characteristics, the numbers of observation decrease drastically due to the data availability. The effects of Time Zone Differences increase significantly, almost tripled comparing model (1) with model (3) and model (5) with model (7) when controlling the firm-level factors. As we can see the explanatory power increase when considering the firm characteristics.

Our estimates are consistent with our expectation that larger time zone differences, as a proxy of information asymmetry, lead to longer completion of the deal. This can be attributed to various channels that contribute to information asymmetry arising from time zone differences. These channels include different business hours, varied interpretations and responses to information, and unequal access to local market information. This finding slightly differs to Bick et al. (2017), which shows that the distance has negative impact on time to completion but positive only for small firms.

Cumulative abnormal returns

The following model is built to estimate the effect of Time Zone Difference on the cumulative abnormal returns (CAR) for the event windows (−1, 1) and (−2, 2) around the announcement date as in Schweizer, Walker and Zhang (2019). We expect a negative effect of Time Zone Difference on the CARs, as the fact that an increase Time Zone Difference results in greater informational asymmetries between acquirer and target.

Table 5 shows different specifications of the equation (2), i.e. only deal controls are considered in Panel A, deal controls and firm controls are included in Panel B, deal controls and macro controls are considered in Panel C, and deal controls, firm controls and macro controls in Panel

D. Regarding to the cumulative abnormal returns, we consider two different event windows, i.e., (-1, 1) and (-2, 2).

The model (1) in Panel A indicates that larger the Time Zone Difference destroys the abnormal return, -0.05%. Regression (1) for the alternative cumulative abnormal returns (-2, 2) shows that the impact of the Time Zone Difference on the acquisition premium is insignificant in our sample. Model (2)-(4) have different specifications compare to Model (1). The effect become larger when controlling both the Year fixed effects and Industry fixed effects. In other words, the effect of Time Zone Difference is 0.000866 on CAR(-1, 1) and -0.00101 on CAR(-2, 2). Both estimates are significant at the 95% confidence level.

When including the firm controls, the lower Time Zone Difference variable has a positive and significant effect on the acquisition premium in model (3) and model (4) for CAR(-1, 1) and model (2)-(4) for CAR(-2, 2). Comparing the effects of Time Zone Difference, the estimates in Panel B seem to have larger effects. Consistent with the results in Panel A and B, our results in Panel C and D also reveal negative impact of the Time Zone Difference. Our results, to some extent, are in line with the impact of geography distance on abnormal acquirer returns in the Uysal, Kedia, and Panchapagesan (2008). In their paper, they document find that acquirers earn significantly higher returns in the M&As transactions in the local area compared to the non-local transactions.

Table 5: Time Zone Difference and cumulative abnormal returns.

Panel A: Add Deal Controls								
VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000581*	-0.000619**	-0.000865**	-0.000866**	-0.000656	-0.000799**	-0.000916*	-0.00101**
	(0.000300)	(0.000299)	(0.000363)	(0.000368)	(0.000400)	(0.000398)	(0.000479)	(0.000481)
Add Deal Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	543	543	543	543	543	543	543	543
R-squared	0.02	0.09	0.403	0.443	0.025	0.093	0.419	0.465

Panel B: Add Deal Controls and Firm Controls								
VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000503	-0.000505	-0.000928**	-0.00114***	-0.00074	-0.000911**	-0.00140**	-0.00173***
	(0.000351)	(0.000335)	(0.000441)	(0.000414)	(0.000461)	(0.000442)	(0.000588)	(0.000534)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Firm Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	332	332	332	332	332	332	332	332
R-squared	0.044	0.193	0.487	0.602	0.037	0.182	0.47	0.614

Panel C: Add Deal Controls and Macro Controls								
VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000573*	-0.000669**	-0.000831**	-0.000880**	-0.000655	-0.000850**	-0.000935*	-0.00106**
	(0.000306)	(0.000305)	(0.000378)	(0.000379)	(0.000422)	(0.000422)	(0.000520)	(0.000522)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Macro Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	585	585	585	585	585	585	585	585
R-squared	0.012	0.067	0.352	0.394	0.009	0.062	0.355	0.395
Panel D: Add Deal Controls, Firm Controls and Macro Controls								
VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000474	-0.000495	-0.000711*	-0.000951**	-0.000624	-0.000784*	-0.00104*	-0.00137***
	(0.000333)	(0.000320)	(0.000426)	(0.000394)	(0.000440)	(0.000424)	(0.000567)	(0.000512)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Firm Controls	√	√	√	√	√	√	√	√
Add Macro Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	355	355	355	355	355	355	355	355
R-squared	0.048	0.18	0.45	0.576	0.049	0.175	0.44	0.59

Note: This table shows the effect of Time zone on the acquisition premium. The acquisition premium is defined as acquirer's abnormal return for event windows (−1, 1) and (−2, 2) around the announcement date before the announcement date to the completion date. Time Zone Difference equals the number of differences in time zone between the target and the acquirer. The standard errors are reported in parentheses for each regression.

*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

Method of payment

The results presented in Table 6, which displays the outcomes of logit regressions for the method of payment, provide insights into the relationship between time zone difference and the choice of payment method in cross-border mergers and acquisitions (M&A) in China. The findings reveal that as the time zone difference increases, there is a negative impact on the likelihood of using cash payment, while the probability of adopting stock payment significantly rises. The results for regression models (1 to 6 for cash payment, and 7 to 12 for stock payment) presented in Table 6 indicate that time zone difference plays a crucial role in determining the choice of payment method in cross-border M&As in China, with larger time zone differences reducing the likelihood of cash payment and increasing the likelihood of stock payment.

The observed results can be explained in the context of asymmetric information and the role it plays in M&A transactions. The use of cash payment in M&As is often associated with managers possessing superior information about the deal, giving them confidence to settle the acquisition in cash. However, when the time zone difference is larger, it amplifies information asymmetry between the acquirer and the target firm. In such cases, the likelihood of using cash payment diminishes as managers may have limited access to timely information, and uncertainties regarding the deal may arise, which is consistent with Luypaert and Van Caneghem (2017) that targets characterized by lower uncertainty are more likely to be settled with cash. As a result, the preference shifts towards stock payment, which allows for the alignment of interests between the acquiring and target firms, bridging the information gap and mitigating potential risks associated with asymmetric information.

Table 6: Method of payment logit regressions.

VARIABLES	Cash Payment (=1)						Stock Payment (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time Zone Difference	-0.0252***	-0.0170**	-0.0398	-0.0163**	-0.00637	-0.0421	0.153***	0.161***	0.641**	0.152***	0.174***	0.962**
	(0.00790)	(0.00806)	(0.0333)	(0.00816)	(0.00962)	(0.0339)	(0.0405)	(0.0410)	(0.276)	(0.0412)	(0.0515)	(0.459)
Add Deal Controls	√	√	√	√	√	√	√	√	√	√	√	√
Add Firm Controls			√			√			√			√
Add Macro Controls				√	√	√				√	√	√
Year FEs		√	√	√	√	√		√	√	√	√	√
Industry FEs			√		√	√			√		√	√
Observations	3,888	3,888	451	3,743	3,457	412	3,888	3,262	75	3,117	1,561	61

Note: This table reports the results of logistic regression analysis of using different deal payment. The dependent variable equal to 1 if the payment uses the cash payment, as in Model (1) to Model (6); equal to 1 if the payment uses the stock payment, as in Model (7) to Model (12). Time Zone Difference equals the number of differences in time zone between the target and the acquirer. The standard errors are reported in parentheses for each regression.

*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

6. Robustness check

As we can see from the data, around one third of the targets in Chinese cross-border merger and acquisition transaction were from Hong Kong, SAR and United States. To ensure that our results are not driven by transactions in these two areas. This section performs three additional models to check the robustness by excluding the targets in the Hong Kong, SAR and the United States.

The results reported in Table 7, Table 8 and Table 9 are the alternatives to the Table 4, Table 5, and Table 6, respectively. Overall, from the tables, we can see the results are consistent and qualitatively the same with the main results in the Section 4.

The results from Table 7 shows higher impacts of the time zone in the days to completion. However, the results also present insignificant effects of time zone in model (3), (4), (7) and (8). The results in Table 8 are consistent with those in Table 5 with the exception of models with deal controls and macro controls in the Panel C.

Table 9 also shows that larger time zone differences lead to less likely to adopt the cash payment and more likely to use the stock payment in M&As transactions. Moreover, we can see that the absolute values of the coefficients in the Table 9 are consistently larger than those in Table 6. In other words, the effects are higher when excludes the Hong Kong and U.S. transactions.

7. Conclusion

Time zone difference is gaining increasing attention in the area of financial investment and financial geographic. In economic literature, the time zone difference has been found to have adverse effect on the trade. It also negatively impacts the international tourism. In this paper, we try to test the main hypothesis that the time zone difference has negative effect on the M&A transactions.

We adopt the M&A data from Bureau van Dijk's Zephyr databases, which collects all the M&As information associates with a Chinese acquire. We aim to answer following research questions: 1) Is the time zone difference associated with the time to be successfully implemented, positively or negatively? 2) Does time zone difference impact the acquisition premium? 3) How does the time zone difference impact methods of payment in the M&A transactions?

Our evidence extends prior studies that examine the factors that affect the M&As. Our results, firstly, show that the time zone difference has significantly positive effect on the days to deal completion. Secondly, that is, larger time zone difference leads to lower cumulative abnormal returns in two different measures. Thirdly, the higher time zone difference reduces the likelihood to use the cash payment, while increases the likelihood to use the stock payment in the cross-border mergers and acquisitions in China. We, finally, exclude the effects in the Hong Kong, SAR and United States as robustness tests. Evidence shows that the results are qualitatively unchanged, showing the time zone difference negatively affect the cross-border M&A transactions.

The results have significant and important implications in M&A transactions; hence the main implication of the findings is that time zone difference should be taken into account. This study implies that time zone differences are harmful to cross-border M&A. We further would like to suggest the managers to consider the time zone when they choose the targets in cross-border M&A integration.

As the fact that China is a developing country, the cross-border M&A transactions are not as active as those in developed countries, e.g., the US and the UK. Due to accessibility of the data, we limit our sample in China. The negative effect of the time zone difference in China comes from the information asymmetry. The financial service is much mature in the US, does the time zone difference also matter in the US, where the integration of information systems is more developed? For further study, we will examine the cross-border M&As in the US by utilizing the Securities Data Company (SDC) Platinum database.

Appendices

Table 7: Time Zone Difference and Days to Completion.

VARIABLES	Days to Completion							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Time Zone Difference	7.110***	7.093***	10.30	12.02	6.888***	6.946***	16.11	13.38
	(2.330)	(2.308)	(10.88)	(10.39)	(2.403)	(2.410)	(11.07)	(11.17)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Firm Controls			√	√			√	√
Add Macro Controls					√	√	√	√
Year FEs		√		√		√		√
Industry FEs	√	√	√	√	√	√	√	√
Observations	3,340	3,340	496	496	3,202	3,202	462	462
R-squared	0.223	0.254	0.461	0.559	0.235	0.244	0.486	0.525

Note: This table shows the effect of Time zone on the days to deal completion (exclude the targets in the US and Hong Kong). Days to Completion is defined as the number of days from the deal announcement to the deal completion. Time Zone Difference equals the number of differences in time zone between the target and the acquirer. The standard errors are reported in parentheses for each regression.

*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

Table 8: Time Zone Difference and cumulative abnormal returns.

Panel A: Add Deal Controls								
VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000629*	-0.000662*	-0.000553	-0.000587	-0.000444	-0.000570	-0.000207	-0.000482
	(0.000354)	(0.000351)	(0.000443)	(0.000447)	(0.000474)	(0.000473)	(0.000578)	(0.000579)
Add Deal Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	448	448	448	448	448	448	448	448
R-squared	0.023	0.114	0.440	0.497	0.022	0.100	0.467	0.528

Panel B: Add Deal Controls and Firm Controls								
VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000709	-0.000657	-0.000997*	-0.00129**	-0.000853	-0.00100*	-0.000940	-0.00139*
	(0.000438)	(0.000412)	(0.000590)	(0.000530)	(0.000581)	(0.000552)	(0.000806)	(0.000723)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Firm Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	271	271	271	271	271	271	271	271
R-squared	0.051	0.240	0.525	0.676	0.042	0.219	0.491	0.654

Panel C: Add Deal Controls and Macro Controls		
VARIABLES	cumulative abnormal returns (-1, 1)	cumulative abnormal returns (-2, 2)

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000360	-0.000512	-0.000222	-0.000311	-4.57e-05	-0.000278	0.000282	-1.46e-05
	(0.000343)	(0.000340)	(0.000429)	(0.000426)	(0.000464)	(0.000461)	(0.000566)	(0.000561)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Macro Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	473	473	473	473	473	473	473	473
R-squared	0.010	0.097	0.419	0.479	0.005	0.085	0.443	0.502

Panel D: Add Deal Controls, Firm Controls and Macro Controls

VARIABLES	cumulative abnormal returns (-1, 1)				cumulative abnormal returns (-2, 2)			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Time Zone Difference	-0.000691	-0.000662*	-0.000887	-0.00114**	-0.000823	-0.000916*	-0.000698	-0.00119*
	(0.000419)	(0.000397)	(0.000567)	(0.000510)	(0.000560)	(0.000535)	(0.000777)	(0.000696)
Add Deal Controls	√	√	√	√	√	√	√	√
Add Firm Controls	√	√	√	√	√	√	√	√
Add Macro Controls	√	√	√	√	√	√	√	√
Year FEs		√		√		√		√
Industry FEs			√	√			√	√
Observations	283	283	283	283	283	283	283	283
R-squared	0.061	0.230	0.507	0.659	0.056	0.210	0.480	0.644

Note: This table shows the effect of Time zone on the acquisition premium (exclude the targets in the US and Hong Kong). The acquisition premium is defined as acquirer's abnormal return for event windows (−1, 1) and (−2, 2) around the announcement date before the announcement date to the completion date. Time Zone Difference equals the number of differences in time zone between the target and the acquirer. The standard errors are reported in parentheses for each regression.

*** Indicates statistical significance at the 1% level.

** Indicates statistical significance at the 5% level.

* Indicates statistical significance at the 10% level.

Table 9: Method of payment logit regressions.

VARIABLES	Cash Payment (=1)						Stock Payment (=1)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Time Zone Difference	-0.0484***	-0.0402***	-0.114***	-0.0399***	-0.0303***	-0.120***	0.163***	0.188***	1.213**	0.179***	0.198***	1.509**
	(0.00841)	(0.00862)	(0.0423)	(0.00874)	(0.0104)	(0.0435)	(0.0427)	(0.0446)	(0.528)	(0.0451)	(0.0561)	(0.694)
Add Deal Controls	√	√	√	√	√	√	√	√	√	√	√	√
Add Firm Controls			√			√			√			√
Add Macro Controls				√	√	√				√	√	√
Year FEs		√	√	√	√	√		√	√	√	√	√
Industry FEs			√		√	√			√		√	√
Observations	3,370	3,365	363	3,227	2,925	324	3,370	2,647	65	2,509	1,217	65

Note: This table reports the results of logistic regression analysis of using different deal payment (exclude the targets in the US and Hong Kong). The dependent variable equal to 1 if the payment uses the cash payment, as in Model (1) to Model (6); equal to 1 if the payment uses the stock payment, as in Model (7) to Model (12). Time Zone Difference equals the number of differences in time zone between the target and the acquirer. The standard errors are reported in parentheses for each regression.

*** Indicates statistical significance at the 1% level.

** Indicates statistical significance at the 5% level.

* Indicates statistical significance at the 10% level.

Chapter 2. Does the investor attention improve the covariance matrix forecasting ability?

1. Introduction

Portfolio diversification is essential for optimizing investment and manage risk level in financial analysis. Modelling assets covariance is important to use in portfolio diversification theory, which suggests capturing an optimal portfolio by determining the efficient frontier. Many financial applications for both academics and practitioners require the estimation of the covariance matrix on various assets.

Previous studies suggested that covariance matrix forecasting is an important component in financial risk management, which is widely used in value-at-risk models as well, especially after European Economic Community countries was encouraged by their central banks to conduct the value-at-risk (VaR) measures in 1997. The importance of analysing between returns and volatility in financial market have also been emphasized by BIS and Basle Committee, the central bank based on their value-at-risk performance to calculate the capital adequacy requirements for those banks. Hendricks (1996) provides an extensive evaluation of alternative VaR models utilizing the portfolio of foreign exchange rates, even though he has not examined the covariance forecasting. Several applications of this exist in previous literature to examine the VaR model for asset portfolios from various multivariate volatility models (see, Alexander and Leigh, 1996; Jackson, Maude and Perraudin, 1997; Lopez, Walter; 2000).

According to Hsieh (1993), both of dynamic volatility and conditional density based on covariance matrix forecasting can serve a better explanation of short-term price volatility than unconditional density.

Merton (1987) mentions that investor cognizance has a significant impact on asset pricing. Recently, Barber and Odean (2008) find that an increased retail investor attention can affect stock returns. However, investor attention is difficult to capture and quantify it appropriately. To solve the substantial challenges, most investigations use indirect measures to capture investor attention, such as extreme returns, abnormal trading volume, news events, adverting expenses, and headlines (e.g., Barber and Oden, 2008; Yuan, 2008; Chemmanur and Yan, 2009; Lou, 2008; Peng and Xiong, 2008). However, those indirect approaches cannot indicate investor attention properly. For instance, the extreme returns and abnormal trading volume could be affected on other factors not only investor sentiment, additionally the news, headlines, and advertising cannot catch attention unless investors allocate sufficient attention to read it (Da, Engelberg, & Gao, 2011). As Kahneman (1973) argues that 'attention is a scarce cognitive resource'. Measurement of investor attention still is a challengeable task.

Generally, Google search volume index (GSVI, hereafter) can be treated as a direct measure of investor attention, if investor search the stock index on Google, which reflects the investor paying attention indeed rather than any other irrelevant purposes with investment. Recent research also concludes that GSVI has appeared predictive powers in varying fields and enables to capture individual investor attention. Ginsberg et al. (2009) show that GSVI has ability to enhance influenza epidemics forecasting. Then, the relationship between GSVI and economic activities is proved by Varian and Choi (2012), GSVI has the potential to predicate unemployment claims, travel planning, automobile sales and market confidence. The predicative ability of GSVI in financial studies is popular to investigate. Da et al. (2011) suggest that Google search volume can capture retail investors attention more directly and timely fashion compares with other approaches for capturing investor attention. Stream of literature investigates the stock market consequence of information demand by using GSVI (e.g., see Vlastakis and Markellos, 2012; Siganos, 2013; Chronopoulos, Papadimitriou, and Vlastakis, 2015). In addition, the relationship between investor attention measures by GSVI and asset pricing is more popular to investigate (e.g., see Joseph, Wintoki, and Zhang, 2011; Bank, Larch, and Peter, 2011; Vozlyublennaia, 2014; Dimpfl and Jank, 2016; Ding and Hou, 2015).

To shed more light on the predicative power of the novel variable of GSVI in stock market, the increased number of studies analyse the GSVI to associate with stock returns, liquidity and stock market information is needed. This research aims to assess the investor attention by using Google search volume index in determining its effect on stock covariance forecasting, considering whether investor behavior can empirically enhance the predictability of covariance matrix forecasting in stock market. There are several explanations of why GSI reveals stock price volatility. Firstly, increased investor attention, as reflected by higher search volumes, could lead to herding behavior in the stock market, leading to increased trading activity and higher stock price volatility. Secondly, higher attention levels may lead to increased noise trading, where investors make decisions based on non-fundamental factors such as popularity or recent news. Noise traders can introduce additional volatility into stock prices, particularly when attention-driven trading dominates the market. The basic assumption in this study, which is people who search a stock's information in Google, can be treated have direct interest in this company stock. Option-implied information is effective to predicate future stock volatility. The variable of option-implied information also is relevant to this study, which is expected to enhance the covariance forecasting performance and to obtain a possible more accurate predicating result.

The data period in this work is from start of the year in 2007 to the end of year in 2016. In many cases, the higher frequency data always has more accurate predictive power in financial market research. The investor attention in this study is measured by the daily Google search volume index. The normalized time-series search index can be captured at different frequencies and based on different regions in Google Trends, a web-based tool provided by Google, i.e., *https://trends.google.com/trends*/. It allows users to explore and analyze the popularity and search interest of specific search terms or topics over a certain period of time. Google Trends provides insights into the relative search volume of particular keywords, giving users an understanding of how the popularity of a specific topic or search term has changed over time. It is necessary to know that the term of normalized represents the sets of searches to divide the accumulated searches in which depend on the searching frequency.

In this study, the search queries are based on the abbreviation of those five European stock indices to search into Google Trends, which are CAC 40 (France), AEX (Netherlands), DAX (Germany), FTSE 100 (UK), and SMI (Switzerland). The advantages of using stock index in this study have two aspects. Stock index is composed by the top value of companies in one market, which provides an efficient approach to gauge the condition of the market. On the other hand, selecting appropriate search terms to download is crucial for every case in Google Trends. Da et al. (2011) introduce that using ticker symbols is a preferable choice to be searching query, as it is more direct and unambiguous to get investors' attention. The alternative for searching key word is using company names, Vlastakis and Markellos (2012) argue that although searching company names in query contains irrelevant component, these components can be assumed as random noise or naturally deterministic. This study avoids query searching conflict by utilizing official abbreviation of the five stock indices as search queries in Google Trends. In addition, the other data types in this work such as daily stock returns and implied volatility are obtained from the Thomson Reuters Datastream.

The remaining sections are organized as follows. Section 2 includes the literature review, and the section 3 develops the hypothesis to be tested in this study. Section 4 and 5 present the methodology and data, respectively. The results are shown in the Section 6. Last section concludes.

2. Literature Review

The literature review will focus on three areas, the first part will try to review the recent covariance forecasting studies, second will aim to see how the investor attention been applied in the finance and following with the more specific studies in the application of google trends, including volatility models that have been using google trends.

2.1 Covariance Forecasting

Covariance matrix forecasting is an important component in financial risk management, so not surprisingly that a plenty of empirical literature exists in the field of volatility forecast. Several applications of this exist in previous literature to examine the VaR model for asset portfolios from various multivariate volatility models (see, Alexander and Leigh, 1996; Jackson, Maude and Perraudin, 1997; Lopez and Walter, 2000).

Literatures that show high-frequency financial data can lead to more precise and accurate measurement and forecast of the unobservable asset volatility than that using only daily data (Bollerslev, Kretschmer and Pigorsch, 2009), especially models in the HAR-RV framework (Corsi, 2009). A lot of studies also illustrate the advantages of option pricing using high-frequency financial data (Taylor and Xu 1995; Christensen and Prabhala, 1994; Stentoft, 2008; Corsi, Fusari and La Vecchia, 2013; Majewski, Bormetti and Corsi, 2015; Christoffersen, Feunou, Jacobs and Meddahi, 2014). In view of the review of the literature, the following research questions are identified and proposed for this research. Kroner and Ng (1998) indicate the importance of time-varying covariance between asset returns in financial market, which is a key concept in financial market especially in risk management, portfolio selection and hedging. There are various multivariate volatility models in the estimation of asset covariance and covariance forecasting. They also suggest that the selection of multivariate volatility models might result in different results in the applications of dynamic covariance forecasting. Intuitively, a common way for covariance forecasting is based on the rolling fixed-period covariance matrix as a basis of the covariance in the future.

Recently, forecasting covariance matrices by has relatively parsimonious been done to implement multivariate generalized autoregressive conditional heteroskedastic models (MGARCH). Based on the research from Engle and Kroner (1982), the BEKK-GARCH model introduced by extending the ARCH model by Engle (1982) and the univariate GARCH model by Bollerslev (1986) is more available to impose the conditional positive covariance matrices. León and Rubia (2002) try to adopt to O-GARCH and the MGARCH, they find that both models perform well when applies to the Intradaily Electricity Spot Prices. Bauer and Vorkink (2011) develop the multivariate heterogeneous autoregressive (HAR) model of Corsi and Reno (2009). However, it seems that, empirically, studies have found difficult to explain the parameters as covariance matrices have been logarithm transformed. Čech and Baruník (2017) utilize the tick data on 15 liquid and high market capitalization in US market, they find that their model, Generalized HAR model outperforms the HAR, VARFIMA model in the context of high frequency data.

Laurent, Rombouts and Violante (2013) evaluate the 24 multivariate GARCH models and rank them based on the loss function. In their paper, Laurent, Rombouts and Violante (2012) examine 10 stocks in US for forecasting accuracy of a number of models. Comparing the forecasting ability on the Model Confidence Set and the Superior Predictive Ability tests, which will be adopted in our study, they find that DCC normally performs the best. However, they also suggest that although DCC GARCH model and orthogonal GARCH model considered the leverage effect and long memory characteristics might also have worse performance during periods of financial crisis. Santos and Moura (2014) apply the DCC GARCH model to construct a strategy for S&P 100 market, their result shows that this would be conduct a riskier portfolio compared to the benchmark approaches. More recently, Zakamulin (2015) indicates significant differences between various covariance matrix forecasting methodologies. Comparing the mean squared forecast error, it is evident that the DCC-GARCH model outperforms the GO-GARCH model.

Recently, the predictive ability of implied volatility forecasts also been verified by Kourtis, Markellos, and Symeonidis (2016), the implied volatility has empirical significantly effects to enhance international portfolio choices compare with others historical methods. Those findings not only have been proved in stock market, also has been proposed in forecasting foreign exchange volatility.

2.2 Investor Attention

Individuals have a scarce and limited attention to devote to investment, generally, attention influence on investment behavior from two approaches on which depends the extent of captured attention. Devoting little attention to the investment information may lead to a dull reaction or make an irrational or distracted decision but directing too much attention to (probably irrelevant and stale) information can result in an overreaction or herd behaviour.

Recently, more studies provided the evidence that limited attention can influence on asset pricing and dynamics. However, in reality, attention is a scarce cognitive resource (Kahneman, 1973). In order to solve this substantial challenge, recent researchers tend to capture investor attention by using indirect approaches.

The popularity of using social media to predict real world is highly increased, recent literature does identify a link between the direct attention measures from social media and social science discipline. As outlined in a literature review by Barber and Odean (2008), most investors are prone to get the aid from computer to search available common stocks, then set decision for buying stocks. Social media outlets are unique in the sense that they offer users direct and immediate interaction and produce value-relevant content which is incremental to what is revealed through traditional news channels (Chen et al., 2014). By contrast, previous research found no evidence to insist on any association between social media and stock movement (see, e.g., Tumarkin and Whitelaw 2001, Antweiler and Frank 2004, Das and Chen 2007). However, social media outlets have evolved radically in recent times, which can be construed as a form of collective wisdom, providing an enlarged and more meaningful channel through which users share information and ideas. Near contemporary research shows that social media is invariably more accurate than other techniques in extracting diffuse information, such as through surveys and opinions polls.

Twitter can be taken as a popular social network which provides an online micro-blogging service. Every published tweet can be extracted on the platform of Twitter. Recently, Twitter has attracted the attention of many corporations due to its use in filtering news updates by news organisations. A wide range of companies use Twitter to advertise their products or publicise information to stakeholders (Asur and Huberman, 2010). Asur and Huberman (2010) used the rate of chatter from 3 million tweets to construct a linear regression model to predict movies box office revenues in advance of their release. There is also a strong correlation between the amount of attention given to a topic and its subsequent future ranking. A similar relationship is noted whereby in financial markets the content of social media strongly predicts future stock returns (Chen et al., 2014). Moreover, by analysing samples from the NYSE and NASDAQ stock exchanges, it demonstrates that firms with official Twitter accounts exhibit a much higher comovement than those without such accounts (Liu, Wu, Li, and Li, 2015). Bollen, Mao and Pepe (2010) investigated whether the text content of large-scale Twitter feeds affect the value of the DJIA (the Dow Jones Industrial Average). They mainly gauged optimistic and pessimistic moods by the tracking method which is named OpinionFinder. In addition, they deployed the mood tracking tool that is called Google-Profile of Mood States, to tabulate mood in six dimensions (calm, alert, sure, vital, kind and happy).

Wikipedia functions as a public web to provide a variety of information to users, allowing users to easily edit the content. This data of editing frequency can be accessed in Wikipedia Statistics. Rubin and Rubin (2010) analyse the cross-sectional variation about information in 30 Dow Jones Index firms via measuring the frequency of editing Wikipedia. They report that the more is the enhanced frequency of editing then the fewer are the errors that result from the forecast stock returns. Moreover, the positive correlation between stock spread changes alongside the editing frequency of Wikipedia was proved in that paper.

Google as a digital data facilitation company, which achieved the most common and popular search engine compare with other engines in Europe, UK, and USA, also it was awarded as the most visited site according to Internet Traffic from 2010 to 2015. Google Trends provides the normalized search frequency of a specific search-term entered into the whole search volume in Google. The representation can be grouped with the horizontal axis in which shows time, and vertical axis that represents the normalized numbers of searching. After the announcement of Google Trends in 2006, it has been broadly utilized in academia research. One of the most significant findings is from Ginsberg et al. (2009), they show that GSVI has ability to enhance influenza epidemics forecasting, the influenza could be predicted two weeks forward the CDC report. The Google Chief Economist Hal Varian presumes that GSVI is able to describe many economic activities; this study is processed by Choi and Varian (2009). They find that GSVI has power to predicate house sales and tourism tendency. Then, the study of Choi and Varian (2012), they indicate that GSVI has the potential to predicate other more economy activities such as unemployment claims, travel planning, automobile sales and market confidence.

2.3 Google Trends Application

Recently, more studies explored the association between GSVI as measure of investor attention and the influence on financial market in the modern information age. The relationship between GSVI and foreign currency market is analysed by Smith (2012), GSVI has ability to predict volatility of the foreign currency market by searching particular keywords such as 'financial crisis', 'economic crisis', and 'recession'. The significantly relations between those keywords and currency volatility appear the incremental predictive power of GSVI in foreign currency market. Goddard, Kita, and Wang (2015) indicate investor attention is a priced risk factor for foreign exchange rate by measuring investor attention using GSVI and the dynamics of foreign currency exchange rate. They find the GSVI for seven currency pairs is related to the currency risk premium, the GSVI is able to forecast currency returns even controlling for the macrocosmic uncertainty and news supply.

In order to investigate the predicative power of GSVI in stock market, stream of literature investigate the stock market consequence of information demand by using GSVI. Searching queries of Initial Public Offerings is important because more attention on IPOs can trigger the abnormal large first-day returns by long-run reversal performance (Da, et al., 2011). Following the different attention measurement, Da et al. (2011) show that GSVI is more efficiently to capture retail investor attention compare with other attention measurement approaches, even though there has correlation between existing proxies and GSVI that still is differ from others. Vlastakis and Markellos (2012) investigate the relationship between information demand and stock volatility using GSVI as a proxy of information demand. Their study finds that the demand of market level information is significantly positive correlated with both of historical and implied volatility and with stock trading volume; this effect is robust even controlling for information supply and market returns. Siganos (2013) shows that the GSVI on firms with potential merger activity can explain large percent of the increased share price before mergers announcement, as the large information demand of such firms on Google. Chronopoulos, Papadimitriou, and Vlastakis (2015) demonstrate the demanding of information that is measured by GSVI whether can enhance stock volatility, finally they derive a better forecasting performance of stock volatility after including the variable of GSVI.

Additionally, the relationship between investor attention measures by GSVI and asset pricing is more popularly to investigate. Joseph, Wintoki, and Zhang (2011) prove the predicative power of GSVI to be a sentiment factor then linking with future stock returns and trading volumes. This study finds that GSVI reliably predicts stock returns and trading volumes in S&P 500 companies. Bank, Larch, and Peter (2011) analyse the relationship between Google search volume index and returns of German stocks. Their finding shows that the increased search volume of a company is followed by temporary higher stock returns, a rising trading activities and increased stock liquidity, especially for lower market capitalization companies. The findings of temporary changes in stock returns following the increased attention which also can be found in Vozlyublennaia (2014), the study determines that not only attention can affect stock performance, bonds and commodities, but the changes of stock returns do influence investor attention also and this impact is long-term. The similar findings are also found by Dimpfl and Jank (2016), they obtain the GSVI to measure the dynamics of individual investor interest and stock volatility. Their findings are in accord with the noise-trader hypothesis, which a higher volatility can lead to a rise investor attention, conversely, the GSVI also can improve the stock volatility forecasting. Based on previous research, Google search volume index has been indicated can capture retail investor attention properly. Ding and Hou (2015) use GVSI on S&P 500 stocks proxy for retail investor to analyse the impact on stock liquidity and shareholder base, they conclude that increased investor attention results in decreased bid-ask spread and a higher turnover rate due to the more attention indicated by a boarder shareholder base.

3. Research Questions and Hypotheses

The main hypothesis in this study is Google Search can capture investor attention; in other words, GSVI is valid to proxy for investor attention in this context. Many literatures indicate that investor attention is an important factor to impact on finance market. I assume that GSVI as a proxy of investor attention can impact on the volatility of European stock market that is represented by the main European five stock indices in this study. In addition, many studies point out option-implied information is effective to predict stock volatility (e.g., Latane and Rendleman, 1976; Byun and Kim, 2013; Jiang and Tian, 2005), hence it seems reasonable to assume that adopting implied volatility could enhance the predictive power for covariance forecasting. Overall, it seems valid to expect that adopting both GSVI and implied volatility can strengthen the predictability of covariance forecasting models in this study.

Generally, the research questions in this study can be expressed as below:

- Can GSVI contribute to covariance matrix forecasting?
- Which multivariate model implements the best performance for covariance forecasting in this context, compares with the two models: Random walk estimation and Heterogeneous Autoregressive model.

4. Methodology

4.1 Econometrics Models

Many conventional models present the difficulties of long memory modelling and forecasting, for instance, FIGARCH models estimate long-range dependence behaviour time-consuming in computation. Random walk estimation will be adopted as the first model for our analysis,

$$X_{t+1} = \alpha_0 X_t + \gamma_t GSVI_t + \mu_{t+1} \tag{1}$$

Corsi (2009) proposes a mixed-frequency hierarchical AR model of which is Heterogeneous Autoregressive (HAR) Model to enhance the volatility predication. Specifically, HAR model as a fractionally integrated model which process the long-memory behavior of realized volatility more relatively parsimonious, where the daily volatility is modelled as a function of lagged daily, weekly, and monthly volatility. Furthermore, Chiriac and Voev (2011) derive to a multivariate extension for covariance modelling, which is the Vector HAR (VHAR) Model. The benefit of VHAR is that the realized covariance can be expressed as a linear correlation of the lagged realized covariance proceed over the three horizons:

$$X_{t+1} = c + \beta_d X_t + \beta_w X_{t-5:t} + \beta_m X_{t-22:t} + \gamma_t GSVI_t + e_{t+1} \tag{2}$$

Where X_t is the vector of all upper triangular elements from the Cholesky decomposition for the covariance matrix. Then, *d* denotes for the daily, *w* for the weekly, and *m* is the monthly frequency, the regressors in different frequency are approximated as: $X_{t-k:\,t} = \frac{1}{k}\sum_{j=0}^{k-1} X_{t-j}$. Moreover, c is constant term, β_d, β_w, β_m are the parameters for frequency elements of the model, and γ_t indicate the estimator for GSVI. However, the drawbacks of VHAR model should be mentioned, all the assets covariances are based on fixed parameters in VHAR model, but in reality, the covariances of the number of assets cannot obey the same dynamics.

4.2 Forecasting Evaluation

Statistical loss functions are used to evaluate the model forecasting performance. In order to compare the out-of-sample forecasting performance of the models, I consider three of the most commonly used multivariate loss functions in this study, the Euclidean distance (L_E), the Frobenius distance (L_F) and the multivariate quasi-likelihood loss function (L_Q). Those loss functions can be specified as follows:

$$L_E = vech\,(\Sigma_t - H_t)' vech\,(\Sigma_t - H_t) \tag{3}$$

$$L_F = Tr\,[(\Sigma_t - H_t)'(\Sigma_t - H_t)] \tag{4}$$

$$L_Q = log|H_t| + Tr[H_t^{-1}\Sigma_t] \tag{5}$$

Where Σ_t is the realized covariance matrix at time *t*, H_t denotes the forecasting covariance matrix at time t by specific models. L_E is Euclidean loss function to compute the forecast error matrix by equally weighted all the unique vector space of *vech* $(\Sigma_t - H_t)$, and *vech* is the operator that stacks all lower triangular portion of the matrix into a vector. The Frobenius distance, L_F, is extended from the mean squared error loss function to the multivariate one, which is defined as the sum of the differences from element-wise square of $\Sigma_t - H_t$. Where Tr is the trace of square matrix, which is the sum of all diagonal elements.

5. Data and implementation

5.1. Data description

5.1.1 Stock Returns

The empirical application is based on five main European stock markets, i.e., CAC 40, AEX, DAX, FTSE 100, and SMI. Our estimation sample ranges from 01 Jan, 2000 to 19 Apr, 2016, with a total of 3904 daily observations. Before the estimation, we have to clean the data. In order to mitigate the noises and (extreme) jumps, we delete first 15 min and last 15 min in each trading day. Table 1 shows the summary statistics for both 5-min stock returns and daily stock returns. You can also find the plots for daily return in Appendix I. As we can see from the table, the stock returns for both high frequency and the low frequency (daily) are leptokurtic. The negative skewness, except the high frequency SMI returns, indicates the higher probability in left tails. In other words, consistent with the theory that people are risk averse, investors are fear of the downside of the markets. The leptokurtic or excess kurtosis (the kurtosis greater than 3) means that the returns exhibit heavy tails, which meets the financial theory and also common among the financial assets.

Table 1: Summary statistics for the stock returns.

	Panel A: High frequency stock returns (5 mins)					
	Mean (*1.0e-05)	Std. dev.	Min	Max	Skewness	Kurtosis
CAC 40	-0.1002	0.0015	-0.0789	0.0875	-0.8264	258.7652
AEX	-0.0669	0.0015	-0.0673	0.082	-0.0454	223.5779
DAX	0.1207	0.0016	-0.0854	0.0722	-0.8133	223.3403
FTSE 100	0.0253	0.0012	-0.0645	0.0588	-0.4483	237.0952
SMI	-0.0187	0.0012	-0.0594	0.0733	0.6549	267.8593
	Panel B: Daily stock returns					
	Mean (*1.0e-03)	Std. dev.	Min	Max	Skewness	Kurtosis
CAC 40	-0.0945	0.0154	-0.1319	0.0961	-0.6465	11.3785
AEX	-0.0631	0.0155	-0.121	0.1011	-0.3958	8.6112
DAX	0.1138	0.0162	-0.1177	0.1048	-0.419	8.8589
FTSE 100	0.0238	0.0128	-0.1361	0.1042	-0.628	15.1146
SMI	-0.0176	0.0121	-0.115	0.0769	-0.4184	10.7598

Table 2 documents the correlations between the stock returns. As seen in the table, the 5-minutes correlations between the markets are not as high as those between lower frequency returns. For example, for the correlations between FTSE 100 and SMI in the 5-minutes sample is low with 0.6493, while it is much higher in the daily frequency, weekly frequency, and monthly frequency, with the values of 0.7929, 0.8116, and 0.8288, respectively.

However, it is surprising that the correlations in the crisis period are higher than those in the pre-crisis and the post-crisis period for all the samples with different frequencies. Let us take the 5-minute sample for example, the correlation between the CAC 40 and AEX equals to 0.9295 in the crisis, while those for pre-crisis and the post-crisis period are 0.8557 and 0.8348, respectively. Moreover, we can also see similar patterns in daily returns, weekly returns and also the monthly returns.

Table 2: Correlations between the stock returns.

	Full sample: 01/01/2000-19/04/2016				Pre-crisis sub-sample: 01/01/2000-31/07/2008				Crisis sub-sample: 01/08/2008-31/12/2009				Post-crisis sub-sample: 1/1/2010-19/04/2016			
	CAC 40	AEX	DAX	FTSE 100	CAC 40	AEX	DAX	FTSE 100	CAC 40	AEX	DAX	FTSE 100	CAC 40	AEX	DAX	FTSE 100
Panel A: 5-min returns																
AEX	0.866				0.8557				0.9295				0.8348			
DAX	0.8319	0.8728			0.8451	0.8611			0.8671	0.8886			0.7855	0.8864		
FTSE100	0.7548	0.7719	0.7667		0.7506	0.7396	0.7398		0.8333	0.8489	0.8336		0.6966	0.7682	0.7682	
SMI	0.6867	0.7113	0.6643	0.6493	0.5157	0.5232	0.4844	0.4882	0.9029	0.9142	0.8595	0.8344	0.784	0.853	0.8397	0.7681
Panel A: Daily returns																
AEX	0.9322				0.9264				0.9563				0.9377			
DAX	0.9072	0.9331			0.9092	0.9294			0.9127	0.9548			0.9065	0.9265		
FTSE100	0.8397	0.8357	0.823		0.8481	0.836	0.8287		0.8809	0.9184	0.8847		0.7881	0.7747	0.765	
SMI	0.8516	0.8604	0.8228	0.7929	0.7882	0.8061	0.7634	0.7476	0.9381	0.9505	0.9262	0.9057	0.9023	0.8922	0.8608	0.7815
Panel A: Weekly returns																
AEX	0.9285				0.9224				0.9448				0.941			
DAX	0.9011	0.925			0.9001	0.9188			0.9107	0.9606			0.8986	0.918		
FTSE100	0.8322	0.8227	0.7998		0.8545	0.8325	0.813		0.8478	0.8838	0.8441		0.7833	0.7745	0.748	
SMI	0.8801	0.8855	0.8388	0.8116	0.8481	0.8595	0.8099	0.802	0.9332	0.9513	0.9189	0.884	0.9013	0.8882	0.8367	0.785
Panel A: Monthly returns																
AEX	0.9287				0.9332				0.942				0.941			
DAX	0.8985	0.927			0.9006	0.9255			0.9374	0.9793			0.8886	0.9035		
FTSE100	0.8508	0.8485	0.8102		0.8939	0.8768	0.8271		0.8883	0.9431	0.922		0.7489	0.7486	0.7082	
SMI	0.8888	0.8859	0.822	0.8288	0.8658	0.8721	0.7976	0.8471	0.9595	0.9596	0.9531	0.9098	0.8678	0.868	0.7864	0.751

5.1.2 Google search volume indices

To the extent that google search volume indices is a considerable measure of investor attention. Our hypothesis is that GSVI improves the covariance forecasting. Figure 1 plots the GSVI in five markets. Specifically, it is our expectation that, except in SMI market, the GSVIs experience their peak in 2008 the time the financial crisis took place. Other jumps can be also found around European sovereign debt crisis 2011-2012 and the selloff in the global stock markets 2015-2016. In the case of FTSE 100 in UK around 2016, high GSVI resulted from the attention of United Kingdom European Union membership referendum. This evidence is consistent with theory of efficient market hypothesis of co-movements among global financial markets (Dias et al., 2020; Dong, Bowers, and Latham, 2013; and Shi, 2022).

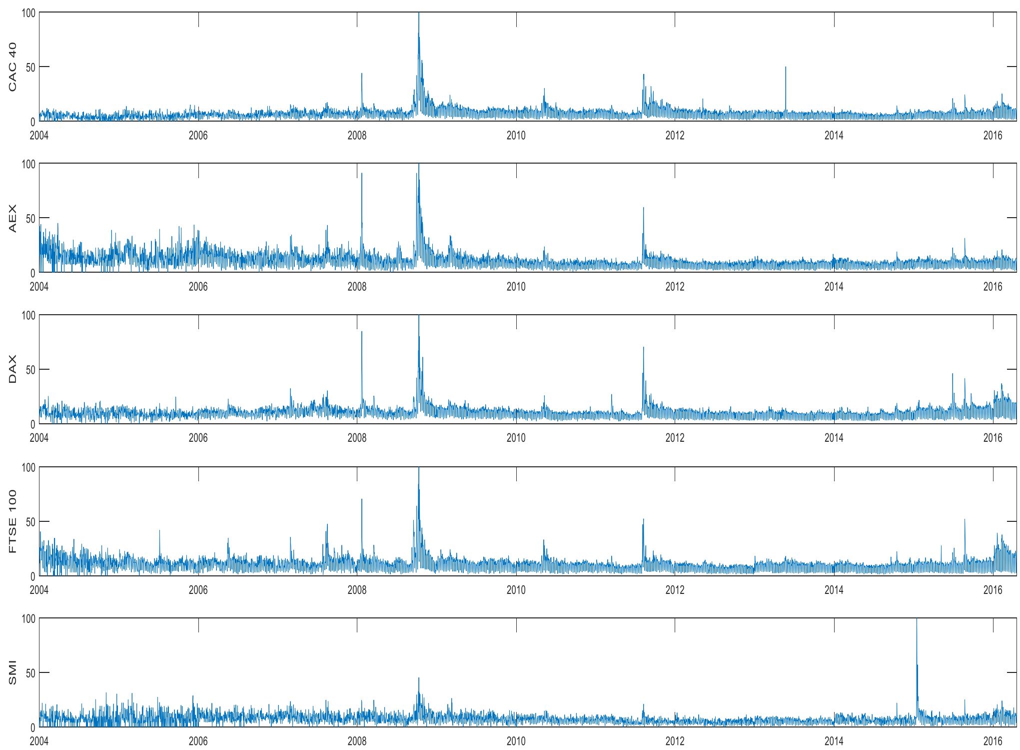


Figure 1: Google search volume indices for five markets 2004-2016.

5.2. Model implementation

This study aims to utilise two alternative methodologies to estimate and forecast the covariance matrix using high-frequency data. I ignore the observations in the dataset corresponding to the trading days when one or more markets are closed, which is consistent with the study of Anderson and Vahid (2013) and Cubadda, Guardabascio and Hecq (2015). The first methodology would be the Random walk estimation (RWE). The second one, the Multivariate Heterogeneous Autoregressive model (VHAR), which being a restricted version of a VAR(22) model in this study. Indeed, the VAR(22) model has $22*N^2$ unknown parameters, whereas the VHAR only needs $3*N^2$ of them. In other words, in our case of 5 indices, 75 parameters are to estimate. In both models, we have each observation is a 5*5 squared covariance matrix. Further investigations will be conducted with google search volume index, these results comparing with those without GSVI will indicate whether GSVI contribute to the forecasting of covariances.

We use a rolling sample of 1,000 observations, leaving 2654 trading days in order to evaluate the 1-day-ahead, 5-day-ahead and 22-day-ahead covariance forecasting accuracy. The results can be found in following section.

6. Results

6.1 Variance and covariance

The variance and covariance are calculated on a 1000-day base. Figure 2 show the variances in five markets over time. They are not as volatile as those from the daily data in other studies. Higher variances can be found around 2008-2012, which resulted from the global financial crisis and the European debt crisis. Summary statistics for realized variances and covariances can be found below,

Table 3: Summary statistics for realized variances and covariances.

	Panel A: realized Variance				
	Mean (e-04)	Min (e-05)	Max (e-04)	Skewness	Kurtosis
CAC 40	2.3837	7.6083	3.8557	-0.1567	1.3032
AEX	2.3554	7.5573	3.7966	-0.2113	1.8883
DAX	2.5636	9.3077	4.3333	-0.0185	1.8069
FTSE 100	1.6293	5.7372	2.6578	-0.0500	1.4424
SMI	1.4969	4.5532	2.7103	0.3328	1.6212
	Panel B: realized Covariance				
	Mean (e-04)	Min (e-05)	Max (e-04)	Skewness	Kurtosis
CAC 40- AEX	2.2266	6.9882	3.5799	-0.1683	1.4746
CAC 40- DAX	2.2557	7.7231	3.7126	-0.1106	1.4744
CAC 40- FTSE 100	1.6946	5.4620	2.7703	-0.1473	1.3194
CAC 40- SMI	1.6601	4.9407	2.9831	0.2451	1.5942
AEX- DAX	2.3089	8.0319	3.6336	-0.1875	1.7501
AEX- FTSE 100	1.7014	5.6187	2.8421	-0.0897	1.5268
AEX- SMI	1.6695	5.0979	2.9991	0.2695	1.7742
DAX- FTSE 100	1.7321	6.2753	2.7649	-0.1651	1.4170
DAX- SMI	1.6709	5.5705	2.9401	0.1696	1.7362
FTSE 100- SMI	1.3035	4.1597	2.3907	0.3539	1.6343

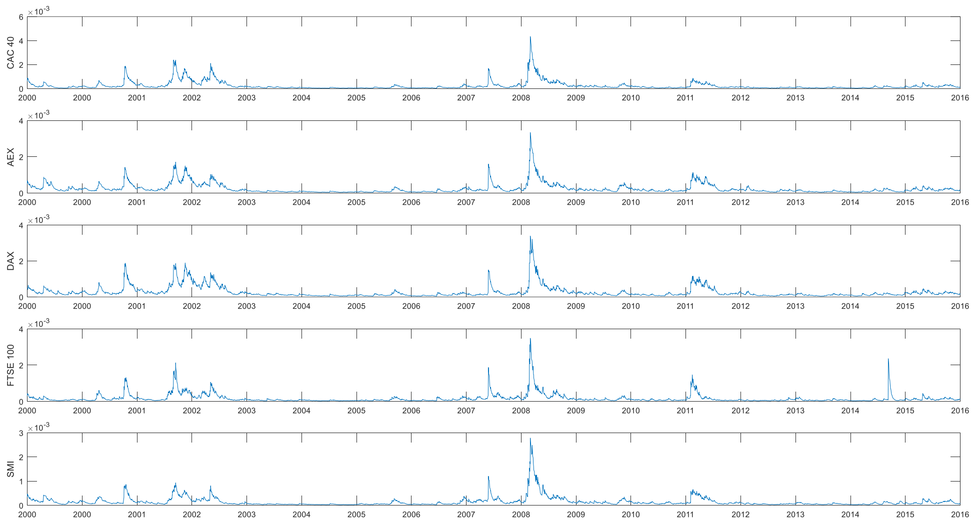


Figure 2: Variances in five markets over time.

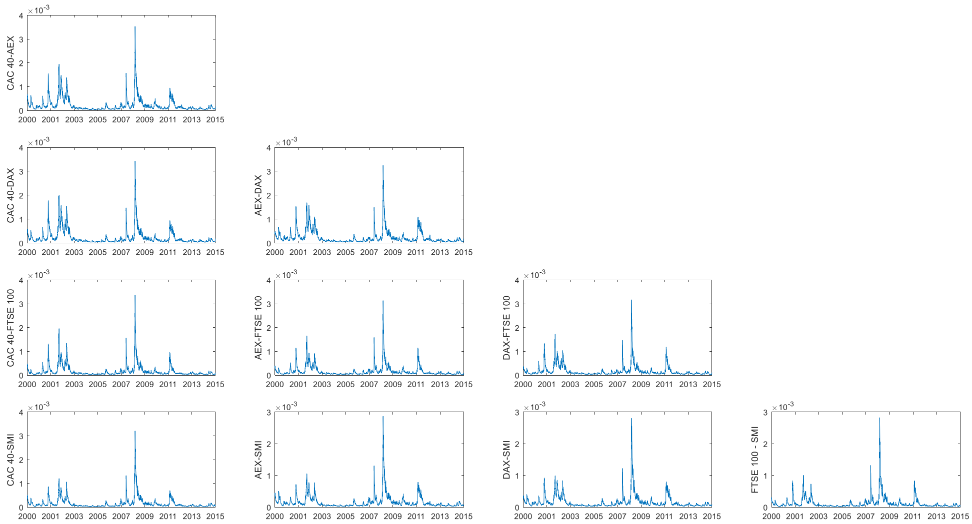


Figure 3: Pairwise Covariance among five markets

We use a rolling sample of 1,000 observations, leaving 2904 trading days in order to evaluate the 1-day-ahead, 5-day-ahead and 22-day-ahead covariance forecasting accuracy.

6.2 In-sample and Out-of-sample Forecasting

6.2.1 In-sample forecast

Table 4: In-Sample Forecast Losses

Models	1-day-ahead forecast			5-day-ahead forecast			22-day-ahead forecast		
	L_E	L_F	L_Q	L_E	L_F	L_Q	L_E	L_F	L_Q
RWE	0.0012	0.0027	-24.6467	0.0519	0.0032	13.859	0.0483	0.0030	157.591
VHAR	0.0076	0.0595	-53.6745	0.0073	0.0713	12.468	0.0076	0.0602	15.623

As we see from the table above, the conclusion seems to differ across different forecast periods. We cannot beat the random walk in terms of L_E and L_F in the 1-day forecast, the L_Q conclude the VHAR model works better than the random walk. However, in the 5-day-ahead forecast and 22-day-ahead forecast, the L_E and L_Q find the VHAR model performs better than RWE, and contrary conclusion is found by L_F.

6.2.2 Out-of-sample forecast

Table 5: Out-of-Sample Forecast Losses

Models	1-day-ahead forecast			5-day-ahead forecast			22-day-ahead forecast		
	L_E	L_F	L_Q	L_E	L_F	L_Q	L_E	L_F	L_Q
RWE	0.0018	0.0032	-20.1146	0.057	0.0036	17.5435	0.0568	0.0034	175.1007
VHAR	0.0086	0.0773	-48.186	0.0086	0.0759	14.331	0.0086	0.0743	18.1667

In the case of 1-day-ahead forecast, we find that RWE performs better than VHAR model in the case of L_E and L_F. However, we can conclude a contrast result in 5-day-ahead forecast and 22-day-ahead forecast in the loss function of L_E and L_Q. Although with mixed results, we do see good performances of the VHAR model. I also plot the time varying covariance matrix through the VHAR model.

6.3 Forecasting with GSVI

The variance and the covariance exhibit the peak around the financial crisis, which look similar with the GSVI shown previously. Therefore, we adopt the GSVI to see whether it contributes to our covariance matrix forecasting. As the GSVIs are only available from 01/01/2004, where we start our sample from. Using the same methodology as we did previously.

6.3.1 In-sample forecast with GSVI

Table 6: In-Sample Forecast Losses with GSVI

Models	1-day-ahead forecast			5-day-ahead forecast			22-day-ahead forecast		
	L_E	L_F	L_Q	L_E	L_F	L_Q	L_E	L_F	L_Q
RWE	0.001092	0.002376	-21.442	0.045672	0.002752	10.81002	0.042504	0.00258	122.921
VHAR	0.006004	0.05117	-45.086	0.005913	0.057753	9.9744	0.006156	0.048762	12.4984

6.3.2 Out-of-sample forecast with GSVI

Table 7: Out-of-Sample Forecast Losses with GSVI

Models	1-day-ahead forecast			5-day-ahead forecast			22-day-ahead forecast		
	L_E	L_F	L_Q	L_E	L_F	L_Q	L_E	L_F	L_Q
RWE	0.001638	0.002816	-17.499	0.05016	0.003096	13.68393	0.049984	0.002924	136.5785
VHAR	0.006794	0.066478	-40.476	0.006966	0.061479	11.4648	0.006966	0.060183	14.53336

From the table above, we see that the losses drop dramatically with the forecasting with google trend data (GSVI) in terms of the In-sample and out-of-sample forecast, which is consistent with our expectation. Especially from the out-of-sample forecast, in the case of $L_{E,}$ nearly 20 percent improvement in the forecasting and 15 percent point improved in terms of the L_F. The results for multivariate quasi-likelihood loss function varies, the performance in 1-day-ahead forecast is worse than the standard VHAR model, and the result does not change too much in terms of the 22-day-ahead forecast. However, it seems VHAR with GSVI model performs better in the case of 5-day-ahead forecast.

7. Conclusion

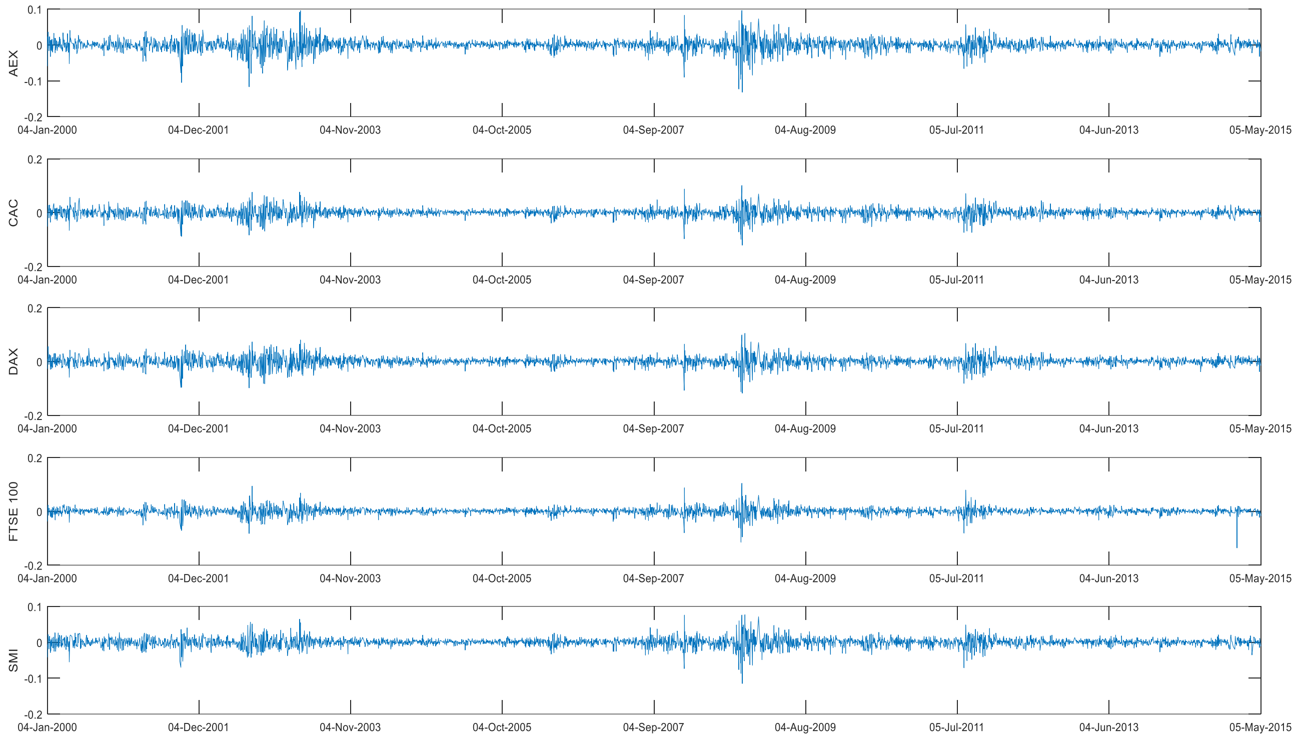
The inclusion of investor attention variables in covariance matrix forecasting has been found to improve the accuracy of predictions. When investors pay more attention to certain stocks or stock indices, it can lead to increased trading activity and liquidity in those stocks or stock indices. Investor attention, reflecting interest and focus that market participants place on specific market indices in our study, serves as a valuable input that captures the flow of information and market sentiment. This information flow, in turn, provides additional insights into the dynamics of market indices movements and the relationships among the indices. By incorporating investor attention variables, i.e., the Google search volume index (GSVI), researchers and practitioners can capture the attention and sentiment of investors towards specific market indices, ultimately influencing stock indices movement and, consequently, the covariance matrix. In this study, we consider the estimation and forecasting for covariance matrix with respect to five major stock markets in the world. Comparing the results with and without google search volume index, we find that the GSVI does contribute and improve the covariance matrix prediction.

In this study, we consider the estimation and forecasting for covariance matrix with respect to five major stock markets in the world. Comparing the results with and without google search volume index, we find that the SVI does contribute and improve the covariance matrix prediction using the multi-variable models-RWE and VHAR models, we also find that using VHAR module has relatively better forecasting performance than RWE module in this study. These findings gap the research of covariance forecasting incorporating considering the investor attention, which have implications in reality. Considering covariance of underlying assets also helps option traders to price and hedge kinds of contingent claims, risk managers and equity analysts always use the covariance forecasts into value-at-risk models for inspecting by their central banks. A portfolio manager pay attention to assets covariance in order to create optimal portfolios.

Considering further studies, some potential ideas would be of interest. Firstly, current study, as well as many other studies such as Symitsi et al. (2018), aggregates the higher frequency returns to 5-minute intraday data. Pooter, Martens and Dijk (2008) indicates that a trade-off between accuracy and potential biases resulted from the market microstructure raise a question of which frequency to use. In their paper, the sampling frequency ranges of 30 to 65 minutes have been confirmed to be the optimal ones. Is 5-minute intraday data an optimal frequency we could adopt in our paper? If not, what frequency should be used in the covariance matrix modelling and forecasting? Additionally, we have estimated and forecasted the covariances for a portfolio of 5 stock markets. Can we be able to extend so for large covariance matrices? This is also of interest to us. In reality, investor attention is difficult to capture, only using GSVI might not be properly indicate it, so it also would be interesting to consider other indirect approaches such as news events, headlines, other social media.

Appendices

Figure 4: The returns over the whole period.



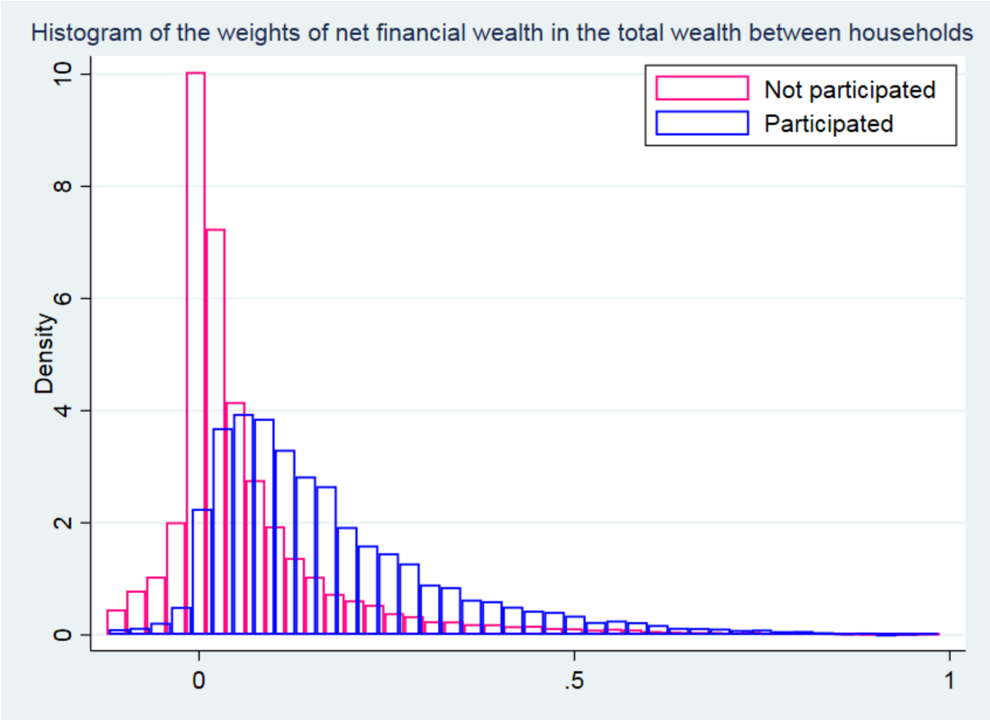
Chapter 3. Stock Market Participation and the Wealth Distribution in the UK

1. Introduction

It is widely accepted that a consequence of changes in the asset markets result in the wealth redistribution: higher asset prices increase the wealth in a household which participated in the asset markets, however, the changes in the asset markets would affect the wealth who does not participate. In practice, household wealth is distributed very unequally (see Brewer and Wren-Lewis, 2016; Crawford, Innes, and O'Dea, 2016, for example).

The figure shows that, in the UK, the households allocate their asset differently. The reason might be due to their risk-aversion, their perception to the future's economy or some constraints (see Guiso, Jappelli and Terlizzese, 1996; Dominitz and Manski, 2007; Brunnermeier and Nagel, 2008; Kapteyn and Teppa, 2011; Guiso, Sapienza and Zingales, 2018). It is worth studying the reason why and how the household build their portfolio. Furthermore, do their portfolio allocation matter to their wealth? The stock market is a commonly utilized method by households to allocate their resources.

Figure 1: Weights of the net financial wealth in the total household wealth between Households



Particularly, in this chapter, we would like to see how the household stock market participation influence the wealth distribution in the UK. In fact, less than half of the households have experience in the stock trading in the U.S., and this number is lower in the UK. Such fact that describes the low stock market participation rate, which refers to 'Limited Stock Market Participation Puzzle' (see Vissing-Jørgensen and Attanasio, 2003; Guiso, Sapienza and Zingales, 2008; Bonaparte and Kumar, 2013), has been received much attention recently.

However, few studies have tried to see how the stock market participation would further affect the wealth of these households and even the whole distribution of the wealth in a country. Theoretically, the wealth distribution can be also affected by several aspects. This can be explained by the difference in the risk aversion between the household (Coen-Pirani, 2004), by the impact of the inflation (e.g., Doepke and Schneider, 2006; Heer and Süssmuth, 2007; and Camera and Chien, 2014). This can be also affected by the participation in the financial markets, such as bond markets, stock markets, housing markets and also the derivatives markets. Our study is more closely and related to Bilias, Georgarakos and Haliassos (2017). Their study has shown that the inequality in stock participation played a significant effect in the overall wealth inequality. Hence, we adopt this view as a starting point. The main objective of this study is to answer: how the stock market participation changes the Wealth distribution in the UK?

To answer this research question, we use the Wealth and Assets Survey (WAS) data. So as to investigate the drivers of the stock market participation, we look at the characteristics of the household by using the information of the reference person in the household, namely the age, education, gender, employment, socio-economic status, and income. Our findings are consistent with the previous studies, including Shum and Faig (2006), Zou and Deng (2019) and Briggs et al (2020).

Our results find that comparing with those have no education qualification, those have education qualifications tend to have more likelihood with different participation measures. Also, we find that the female tends to have less participation in the stock market. Moreover, the employment households are likely to participate into the stock market. Furthermore, we can see the higher income increase the participate in the stock market, either directly or indirectly.

The remainder of the chapter is organized as follows. This study conducts literature review in Section 2. We then illustrate the econometric models that describes the determinants of the stock market participation in Section 3. In Section 4, we present the data, and Section 5 provides the empirical evidence. Section 6 concludes.

2. Literature Review

In this review, we will firstly present the mechanism behind stock market participation, secondly some international empirical evidence, and thirdly some previous evidence from the UK as in our study.

Literature has shown that, the limited participation in the stock and asset market matters for the consumption (e.g. Mankiw and Zeldes, 1991; Vissing-Jørgensen, 2002; Chacko and Viceira 2005; and Gormley, Liu and Zhou, 2010), for the risk premium (see Gormley, Liu, and Zhou, 2010; Ui, 2011; Favilukis, 2013; Horvath, Kaszab and Marsal, 2021), and also for the monetary policy (e.g. Bilbiie, 2008; Bilbiie and Straub, 2013; Airaudo and Bossi, 2017; Ascari, Colciago and Rossi, 2017). Related to our study, the literature on investigating the determinants of the stock market participation is vast. It has garnered considerably attention the stock market participation can be driven by the economy and the characteristics of the household.

From the view of personal characteristics, Hong, Kubik, and Stein (2004) showing that 'social' investors are more likely to invest in stocks, and the participation rates are higher in the stronger sociability states. More specifically, this phenomenon is very substantially different cross-state, and the sociability generates a considerable different participation rate in the "high-participation" states and "low-participation" states. Grinblatt, Keloharju and Linnainmaa (2011) discussed the cognitive ability as a driver of the participation to stock markets. They used that data IQ data and stock registry and mutual fund ownership data around 2000 in Finnish stock market. The probit regressions results have suggested that highest IQ subjects are most likely to participate in the stock market.

Empirically, Changwony, Campbell and Tabner (2015) have shown that those who are weak ties (measured by social group involvement) have higher probability to participate in the stock market. While those who are more frequently taking to neighors do not seems to be more likely to participate in the stock market. More recently, Antoniou, Harris and Zhang (2015) have investigated how the ambiguity could affect the investors to invest in stock markets. Their finding supports the hypothesis that the ambiguity is positively with the outflows in the equity markets. From an economic environmental perspective, Gábor-Tóth and Georgarakos (2019) show that households have less probability invest in stocks directly or indirectly if they have less sensitive to economic policy uncertainty news.

Empirically, the stock market participation puzzle has also been investigated across states. Lee, Jeon and Jo (2020) also show consistent results, finding that U.S. household reduce their stock asset in the portfolios in responding to both US economic policy uncertainty and Chinese economic policy uncertainty. Easley and O'Hara (2009) provide empirical evidence showing that the regulation system in the financial market could affect the market participation rate by influencing the agents' ambiguity. Zou and Deng (2019) use data from the 2012 consumer finance survey in China. Their finding indicates that financial literacy significantly improves the probability of household financial market participation. Giannetti and Wang (2016) documented that the households' participation in the stock market can be affected by the securities market regulation and corporate governance failures. Their evidence showed a negative effect of corporate scandals on the households' willingness to participate in the stock markets.

3. Hypothesis Development

Limited research on stock market participation in the UK calls for further investigation to fill the gap in the literature. While Paya and Wang (2016) have examined factors influencing entry and exit decisions in UK households, there remains a dearth of studies specifically focusing on stock market participation within the UK context. This study seeks to address this gap and contribute valuable insights to our understanding of stock market participation dynamics in the UK. We will develop the hypotheses as follow:

Individuals with higher incomes have greater financial resources and are more likely to engage in stock market investment. Furthermore, previous studies have shown a positive correlation between income levels and stock market participation rates. By testing this hypothesis, we aim to explore the relationship between income and the likelihood of individuals in the UK participating in the stock market.

H1: The income is positively associate with the stock market participation.

Previous studies (Fonseca et al., 2012; Charness and Gneezy, 2012; Hira and Loibl, 2008) suggest potential gender differences in financial decision-making and investment behavior. We aim to further explore this relationship within the UK population. By examining potential gender-related variations in stock market engagement, we contribute to a deeper understanding of the factors that influence individuals' investment decisions and the implications for gender equality in financial markets.

H2: There is a gender effect on stock market participation, with males exhibiting a higher participation rate compared to females.

Research on wealth inequality has highlighted the concentration of wealth among the top percentiles of the distribution. However, the role of stock market participation in exacerbating or mitigating wealth disparities within specific wealth groups remains underexplored. Therefore, there is still a gap in understanding how this participation affects the distribution of wealth across different wealth groups. we aim to investigate whether stock market participation contributes to a more equitable distribution of wealth or if it exacerbates wealth inequalities. We anticipate that stock market participation may have a more pronounced effect on the wealth distribution among lower- and middle-income groups. Individuals within these segments may have limited access to other wealth-building opportunities and rely more heavily on stock market investments to accumulate wealth. Conversely, the impact of stock market participation on the wealth distribution among higher-income groups may be more nuanced. Individuals in these groups may already possess significant wealth and have access to diverse investment options beyond the stock market.

H3: The stock market participation will affect the whole distribution differently.

4. Econometric Framework

There are quite a few factors that will affect whether to participate in the stock market in a household. As the stock market participation indicators are binary variables. Most of the papers accessing the limited stock market participation used logit and probit models (see Bogan, 2008; Kaustia, and Torstila, 2011; Liang, and Guo, 2015; for example). To conduct our empirical analysis, we firstly consider a logit model (Brown, Veld and Veld-Merkoulova, 2018; Zou and Deng, 2019) and probit model (Guiso, Sapienza and Zingales, 2008; and Grinblatt, Keloharju and Linnainmaa (2011), where the dependent variable is a binary variable for stock market participation, to see the determinants of the stock market participation.

Logit Model:

$$\mathrm{Pr}(\mathrm{Participate} = 1) = \frac{\exp(\beta_0 + \beta_1 \mathrm{Gender} + \beta_2 \mathrm{Age} + \cdots + \beta_i \mathrm{income})}{1 + \exp(\beta_0 + \beta_1 \mathrm{Gender} + \beta_2 \mathrm{Age} + \cdots + \beta_i \mathrm{income})} \quad (1)$$

where, the β_1 is the coefficient of the gender effect, β_2 is the parameter for the age band, and $\beta_i$measure the income effect, are the parameters of interest in our study.

Probit Model:

$$Pr(Participate = 1) = \Phi(\gamma_0 + \gamma_1 \text{Gender} + \gamma_2 \text{Age} + \cdots + \gamma_i \text{income})) \qquad (2)$$

where, the γ_1 is the coefficient of the gender effect, γ_2 is the parameter for the age band, and γ_i measure the income effect.

By using the logit model and probit model, we are able to see how the factors contribute to the household stock market participation.

To analyze the impact of stock market participation on wealth distribution, we employ the quantile regression method, following the approach used in Hong, Kubik, and Stein (2004) and Bilias, Georgarakos, and Haliassos (2017). This method allows us to assess the effects of stock market participation across different percentiles of the wealth distribution. This model shares a similar structure to ordinary least square models but focuses on examining the impacts specifically at the i^{th} quantile,

$$y_i = \beta' X_i + \epsilon_i \qquad (3)$$

Where y_i is the total wealth and X_i represents a set of controls, including the dummy for stock market participation, ϵ_i follows i.i.d.

5. Data

In this study, we use the Wealth and Assets Survey data, which interviews the same households every two years and collects detailed data on households' wealth. The dataset is from the UK data service. It is a nationally representative longitudinal survey data set across the Great Britain. This panel dataset has been used to measure the UK wealth inequality in the 2000s (see Hills, et al. 2013; Alvaredo, Atkinson and Morelli, 2016), the connection between monetary policy and wealth inequality (e.g., Mumtaz and Theophilopoulou, 2020). This dataset is similar to the Health and Retirement Survey (HRS) and Survey of Consumer Finances (SCF) in the U.S. and China Household Finance Survey (CHFS) in China. We employ all five waves that have been released. In the wave 1 in 2006-2008 a total of 30,500 households and 53,300 adults were interviewed. Respondents in the survey 1 were invited to take part in Wave 2, as a result the second wave contained 20,000 households and 34,500 adults during the period of July 2008 - June 2010. The third wave of the survey included 21,451 household and 40,396 individuals in the following 2 years, July 2010 – June 2012. Wave 4 covered July 2012 - June 2014 and 20,240 households (46,388 individuals) involved and Wave 5 covered July 2014 - June 2016 and 18,808 households (42,832 individuals) were participated. The WAS employs a complex sampling design to ensure the representation of different population groups. The sample size for each wave may vary to account for the desired level of precision and representativeness across various demographic and socioeconomic characteristics. Due to the fact that some households may no longer be eligible, refuse to participate, or become difficult to contact. To maintain a representative sample over time, Office for National Statistics (ONS) may introduce new households into the survey at different waves.

During the period of 5 waves from 2006 to 2016, the UK experienced various economic conditions. The global financial crisis 2007-2009 had a severe impact on the UK economy, leading to a significant rise in unemployment rates, to approximately 7.8% by the end of 2009, and job losses across various sectors. The labor market experienced a period of economic uncertainty, which could have affected individuals' willingness and ability to participate in the stock market. Following the financial crisis, especially after the European Debt Crisis 2010-2012, the UK economy gradually started to recover, but the labor market recovery was relatively slow. These conditions may also have influenced stock market participation and wealth distribution, as individuals prioritized income stability and financial security. From 2013 onwards, the UK economy experienced a period of modest expansion. However, uncertainties emerged with the announcement of the Brexit referendum in 2016, leading to concerns about the economy and job market, thereby influencing stock market participation and wealth distribution.

We have two different measures of the stock market participation: 1) the direct participate and 2) indirect participate. An investor that has participated in the stock market if the household has any investment in the UK shares, oversea shares, or employee shares. The indirect participation indicates that the household has participated in the Investment Individual Savings Accounts (ISAs), fixed term investment bonds, or unit and investment bonds. Table 1 shows the evolution of the direct participation rate and total (direct + indirect) participation rate across five waves of the survey. It is a striking fact that most households in the UK own no stocks either directly or indirectly. The Wave 2 has highest percentages of direct stockholding and total stockholding compared to other waves. The reason is the stock markets were experiencing a boom during wave 1 and resulted in a high participation in the Wave 2.

Table 1: Stockholding rates in the UK across waves

	Wave 1	Wave 2	Wave 3	Wave 4	Wave 5
Direct stockholding (%)	22.86	25.64	20.91	21.73	20.70
Total stockholding (%)	33.80	39.87	36.67	36.60	35.30
Number of households	30,587	20,165	21,455	20,218	18,808

Notes: Data from Wealth and Assets Survey. The Wave 1 was conducted in Jul 2006 - Jun 2008, the Wave 2 was conducted Jul 2008 - Jun 2010, the Wave 3 was conducted Jul 2010 - Jun 2012, the Wave 4 was conducted Jul 2012 - Jun 2014, and the Wave 5 was conducted Jul 2014 - Jun 2016.

Rather than a pooled cross-section/time-series statistics as in Paya and Wang (2016), the Table 2 present the summary statistics of Wealth types in the UK across waves. In this table we show different measures of wealth in the households, i.e., total household wealth, net household financial wealth, total household physical wealth, total household property wealth, and total household pension value, in which the total household wealth is equal to the sum of the following four wealth measures.

More specific, the net household financial wealth is the difference of gross financial wealth excluding endowments and financial liabilities. As we can see from the table 2, we can see negative values for net household financial wealth in the 10% quantiles in various waves.

The Table 3 presents similar information as in the Table 2, but only for the households participated in stock market. The mean total household wealth for non-participated households is £236,891 in the 2006-2008 and to £364,572 in 2014-2016. In the other words, the total household wealth in participated households, across the 10 years in average, is about 2.41 to 2.52 times higher than those households participated in stock market.

One of the most significant differences is that Total property wealth and Total Pension Wealth in the left tail across five waves are 0 in Table 2, while the two variables in the households participated in the stock markets are much higher, with significantly increase across the time. For example, for variable Total property wealth in wave 1 in lower tail is £37,000 and increase to 72,000 in 2014-2016. The same trend can be seen for the Total Pension Wealth. This, to some extent, support our hypothesis that income is positively associate with the stock market participation.

Table 2: Summary statistics of Wealth types in the UK across waves.

Wealth Type	Mean	median	10%	90%	N
			Panel A: Wave 1 (July 2006 to June 2008)		
Total household wealth	430421.7	228792	3970	996950	30,587
Net financial wealth	58968.76	7500	-3576	150650	30,587
Total Physical Wealth	24719.79	7900	0	65500	30,587
Total property wealth	172727.2	110102	0	382000	30,587
Total Pension Wealth	174006	577962.8	0	439686.8	30,587
			Panel B: Wave 2 (July 2008 to June 2010)		
Total household wealth	473409.6	267653	15600	1071337	20,165
Net financial wealth	68559.94	11900	-3650	176803	20,165
Total Physical Wealth	46329.56	36000	7500	87500	20,165
Total property wealth	119999	174740.9	0	394999	20,165
Total Pension Wealth	28833.62	134355.9	0	332584.3	20,165
			Panel C: Wave 3 (July 2010 and June 2012)		
Total household wealth	485598.9	278523.1	15360	1140570	21,445
Net financial wealth	73535.76	10530	-3970	179400	21,445
Total Physical Wealth	49607.85	38000	7550	91500	21,445
Total property wealth	183778.7	120000	0	400000	21,445
Total Pension Wealth	178676.6	57347.14	0	492927.6	21,445
			Panel D: Wave 4 (July 2012 - June 2014)		
Total household wealth	566394.2	320448.6	16800	1335282	20,218
Net financial wealth	93118.61	12252	-3200	208000	20,218
Total Physical Wealth	51541.46	40000	7900	95500	20,218
Total property wealth	197147.2	125000	0	450000	20,218
Total Pension Wealth	224587	77985.55	0	625934.4	20,218
			Panel E: Wave 5 (July 2014 - June 2016)		
Total household wealth	685419.1	379679.6	18850	1550740	18,808
Net financial wealth	124008.6	13797.5	-3504	233490	18,808
Total Physical Wealth	56333.11	44000	8500	103000	18,808
Total property wealth	233455.3	140000	0	516000	18,808
Total Pension Wealth	271622	102449.4	0	755398.5	18,808

Table 3: Summary statistics of Wealth types for households participated in stock market in the UK across waves.

Wealth Type	Mean	median	10%	90%	N
		Panel A: Wave 1 (July 2006 to June 2008)			
Total household wealth	809434.1	543716.7	143338.8	1583452	10,339
Net financial wealth	147649.2	64500	5038	352601	10,339
Total Physical Wealth	35651.9	22000	0	84001	10,339
Total property wealth	297744.6	210000	37000	598000	10,339
Total Pension Wealth	328388.4	150000	5485	700265.4	10,339
		Panel B: Wave 2 (July 2008 to June 2010)			
Total household wealth	831234.8	562690.8	169337.8	1590582	8,040
Net financial wealth	150560.6	68086.5	5716	347250	8,040
Total Physical Wealth	63848.06	49500	17950	105500	8,040
Total property wealth	288660.2	200000	45000	560000	8,040
Total Pension Wealth	328166	149333.6	7034.5	699123.2	8,040
		Panel C: Wave 3 (July 2010 and June 2012)			
Total household wealth	879578.6	630371.2	185909	1741387	7,864
Net financial wealth	176487.9	74834.5	7350	382105	7,864
Total Physical Wealth	69536.64	53025	19100	115500	7,864
Total property wealth	317640.2	224000	47000	615000	7,864
Total Pension Wealth	315913.8	175022.5	11140.06	766347.2	7,864
		Panel D: Wave 4 (July 2012 - June 2014)			
Total household wealth	1027246	734960.7	220624	2001536	7,406
Net financial wealth	220209.3	87050	9860	453849	7,406
Total Physical Wealth	71885.11	58000	21500	125000	7,406
Total property wealth	338827.7	240000	60000	656236	7,406
Total Pension Wealth	396323.5	234202.2	14880	957528.5	7,406
		Panel E: Wave 5 (July 2014 - June 2016)			
Total household wealth	1273381	879846.6	262180.1	2349988	6,640
Net financial wealth	315648.6	102360	10400	518520.5	6,640
Total Physical Wealth	79712.97	63700	25000	150000	6,640
Total property wealth	403310.2	275000	72000	780000	6,640
Total Pension Wealth	474709.2	300003.1	19458.18	1117378	6,640

6. Empirical results

In this section, we will present various empirical evidence from the econometric models, i.e. logit models and probit models. More important, the results investigating the influence of the stock market participation on the wealth distribution are presented.

6.1. Determinants of the stock market participation.

Table 4: OLS regression of total participation

	Dependent variable is total participation (direct and indirect)				
	(1)	(2)	(3)	(4)	(5)
Age	0.0578***	0.0790***	0.0662***	0.0687***	0.00740***
	(30.89)	(31.71)	(29.25)	(27.83)	(26.64)
Education	-0.143***	-0.217***	-0.112***	-0.163***	-0.174***
	(-29.74)	(-30.94)	(-20.67)	(-27.28)	(-26.16)
Female	-0.0980***	-0.0926***	-0.0703***	-0.101***	-0.0931***
	(-18.00)	(-13.59)	(-11.04)	(-15.30)	(-13.71)
Employment	-0.0314***	-0.0267***	0.0164***	0.00982*	0.0133**
	(-9.37)	(-6.38)	(4.13)	(2.35)	(3.04)
Socio-economic	-0.00129***	-0.00117***	-0.00135***	-0.00133***	-0.00120***
	(-8.99)	(-5.67)	(-6.60)	(-7.37)	(-5.85)
Income			0.0000025***	0.0000010***	0.00000096***
			(38.39)	(22.22)	(21.81)
Constant	0.318***	0.331***	0.0339***	0.159***	0.115***
	(33.09)	(25.26)	(2.60)	(11.70)	(7.69)
Observations	30587	20165	21445	20237	18808

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

As in the WAS data, the education was defined, (1) has education qualification and (4) has no education qualification. Therefore, the negative signs in Table 4 are expected. The female tends to have less participated in the stock market. This is consistent with the psychology theory that females seem to be more risk averse than the males (see Arano, Parker, and Terry, 2010; and Halko, Kaustia, and Alanko, 2012). For the employment variable, as a category variable, it is defined 1 as in employment; 2 as unemployed; and 3 Economically inactive. Therefore, this is consistent with the prior. However, for wave 3, 4 and 5, the unemployed household tend to participate into the stock market after financial crisis. It might be the case those who unemployed are more likely to participate in the post-crisis period. It is defined Managerial & prof. occupations as 1; Intermediate occupations as 2; and Routine & manual occupations as 3 in the socio-economic status, thus we also expect the Managerial & prof. occupations household to have more risk assets in their portfolio. As the WAS doesn't record the income variable for the first two waves, therefore, we interpret the income variable starts from the third wave, we can see the higher income increase the participate in the stock market, either directly or indirectly, with the highest income effect in the third wave 2010- 2012.

Table 5: OLS regression of direct participation.

	Dependent variable is direct participation				
	(1)	(2)	(3)	(4)	(5)
Age	0.0309***	0.0446***	0.0284***	0.0295***	0.00325***
	(18.37)	(19.66)	(14.46)	(13.56)	(13.39)
Education	-0.106***	-0.155***	-0.0699***	-0.101***	-0.104***
	(-24.46)	(-24.33)	(-14.90)	(-19.08)	(-17.96)
Female	-0.0880***	-0.0820***	-0.0595***	-0.0877***	-0.0737***
	(-17.96)	(-13.21)	(-10.77)	(-15.10)	(-12.43)
Employment	-0.0326***	-0.0348***	-0.000104	-0.00678	-0.00209
	(-10.82)	(-9.15)	(-0.03)	(-1.84)	(-0.55)
Socio-economic	-0.000850***	-0.000551***	-0.000529**	-0.000807***	-0.000751***
	(-6.59)	(-2.94)	(-2.97)	(-5.09)	(-4.19)
Income			0.000002***	0.0000009***	0.0000008***
			(34.62)	(21.94)	(21.31)
Constant	0.300***	0.309***	0.0816***	0.188***	0.149***
	(34.68)	(25.87)	(7.21)	(15.67)	(11.38)
Observations	30587	20165	21445	20237	18808

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

Results in Table 5 are consistent with those in Table 4. The significant difference is the employed household tend to participate in the stock market directly. It shows that higher age leads to higher likelihood of the direct participation. Households with education qualifications tend to participate in the stock market directly than those without education qualifications. We can see the coefficients across the waves in Table 5 are less than those in models for total participation. This is the case of quite a few households participated in the stock market indirectly. The negative effect of gender effect is consistent with the Barasinska and Schäfer (2018). This is also in line with the economic theory that women are more risk averse than men (e.g., Charness and Gneezy, 2012).

Table 6: Probit regression of total participation.

	Dependent variable is total participation (direct and indirect)				
	(1)	(2)	(3)	(4)	(5)
Age	0.173***	0.230***	0.203***	0.211***	0.224***
	(30.13)	(31.02)	(28.58)	(27.33)	(25.73)
Education	-0.373***	-0.603***	-0.331***	-0.473***	-0.479***
	(-27.86)	(-30.01)	(-21.05)	(-26.93)	(-25.10)
Female	-0.291***	-0.266***	-0.293***	-0.327***	-0.313***
	(-18.08)	(-13.79)	(-15.66)	(-16.76)	(-15.40)
Employment	-0.106***	-0.0904***	-0.0565***	-0.0291*	-0.0131
	(-10.65)	(-7.54)	(-4.81)	(-2.34)	(-1.01)
Socio-economic	-0.00568***	-0.00461***	-0.00668***	-0.00624***	-0.00618***
	(-10.96)	(-6.79)	(-8.94)	(-9.50)	(-8.02)
Constant	-0.264***	-0.226***	-0.537***	-0.458***	-0.628***
	(-7.47)	(-4.97)	(-11.97)	(-9.60)	(-11.86)
Observations	30587	20165	21445	20239	18808

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

The probit model indicates that the older people are more likely to participate into the stock market, with around 20% increase when the household reference people into a higher age range. The effects seem to be different with those in the OLS models in Table 4. This is because the probit models account for the nonlinear effect in explaining the total stock market participation. The education effect documents that there is a higher probability for those have higher education level to allocate their asset to the financial market. It is not surprising the female tends to less participate into the stock market. The employment and socio-economic status both play their role in the stock market participation. The effects of gender are quite stable among the waves with the effects around -0.3 when accounting the nonlinear effect in the probit models.

Table 7: Probit regression of direct participation.

	Dependent variable is direct participation				
	(1)	(2)	(3)	(4)	(5)
Age	0.108***	0.153***	0.109***	0.108***	0.0122***
	(17.57)	(19.49)	(14.25)	(13.14)	(12.90)
Education	-0.312***	-0.505***	-0.242***	-0.332***	-0.355***
	(-22.44)	(-23.66)	(-14.85)	(-18.56)	(-17.57)
Female	-0.318***	-0.279***	-0.318***	-0.363***	-0.322***
	(-18.23)	(-13.46)	(-15.23)	(-16.83)	(-14.28)
Employment	-0.119***	-0.125***	-0.0872***	-0.0687***	-0.0490***
	(-11.24)	(-9.90)	(-6.88)	(-5.19)	(-3.50)
Socio-economic	-0.00511***	-0.00322***	-0.00475***	-0.00580***	-0.00594***
	(-8.77)	(-4.29)	(-5.55)	(-7.56)	(-6.49)
Constant	-0.266***	-0.257***	-0.516***	-0.365***	-0.549***
	(-6.99)	(-5.25)	(-10.45)	(-7.02)	(-9.45)
Observations	30587	20165	21445	20239	18808

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

The Probit model for direct participation (Table 7) also confirmed with our expectation. Age is still having positive effect in the direct participation, which are different with the effect in the linear models in Table 5. The education plays an influential role determining the direct participation. Among also, education seems to have the highest effect in wave 2, with the coefficient of -0.505, while with the lowest effect in wave 3 (coefficient of -0.242). The gender effects across waves have similar effects on the households' direct participation in the stock market. The employed households are more likely to participate in the stock market in the direct participation.

Table 8: Logit regression of total participation.

	Dependent variable is total participation (direct and indirect)				
	(1)	(2)	(3)	(4)	(5)
Age	0.337***	0.415***	0.375***	0.399***	0.0433***
	(32.59)	(31.94)	(29.56)	(28.95)	(27.36)
Education	-0.960***	-1.201***	-0.823***	-1.176***	-1.145***
	(-31.06)	(-31.61)	(-23.43)	(-29.37)	(-27.32)
Female	-0.469***	-0.427***	-0.477***	-0.537***	-0.506***
	(-17.39)	(-13.38)	(-15.31)	(-16.44)	(-14.85)
Employment	-0.221***	-0.190***	-0.131***	-0.0893***	-0.0843***
	(-12.53)	(-9.29)	(-6.38)	(-4.13)	(-3.71)
Socio-economic	-0.00956***	-0.00763***	-0.0111***	-0.0101***	-0.0104***
	(-9.61)	(-6.24)	(-7.92)	(-8.20)	(-7.02)
Constant	-0.178***	-0.234***	-0.679***	-0.478***	-0.847***
	(-2.94)	(-3.09)	(-8.96)	(-5.86)	(-9.36)
Observations	30587	20165	21445	20239	18808

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

The logit model, to some extent, has shown consistent results with probit model, both showing their nonlinear characteristics compare to the OLS model. However, due to their functional form, the magnitudes tend to slightly different between the two model, with larger impacts on the probability to participate for each variable. The functional form tells us about the relationship between the different measure of participation and the independent variables, where the participation is on the logit scale.

Table 8 reports the Logit regression of total participation. The education and gender both have the most effect of the household participation decision. The coefficients for the education are of high throughout the surveys. Especially in wave 2, the parameter for the education is -1.059, meaning that, comparing with those have no education qualification, those have education qualifications have 1.059 increase in the log-odds of the dependent variable total participation. The effects of gender are quite stable among the waves with the effects around -0.5 to -0.6. The socio-economic status has much less effect in the participation decision.

Table 9: Logit regression of direct participation.

	Dependent variable is direct participation				
	(1)	(2)	(3)	(4)	(5)
Age	0.223***	0.288***	0.209***	0.218***	0.0245***
	(19.65)	(20.63)	(14.62)	(14.28)	(13.90)
Education	-0.788***	-1.059***	-0.550***	-0.832***	-0.845***
	(-22.80)	(-24.59)	(-13.83)	(-17.95)	(-17.11)
Female	-0.542***	-0.470***	-0.556***	-0.634***	-0.562***
	(-17.61)	(-13.14)	(-14.92)	(-16.48)	(-13.94)
Employment	-0.249***	-0.247***	-0.173***	-0.149***	-0.123***
	(-12.67)	(-11.07)	(-7.31)	(-6.09)	(-4.78)
Socio-economic	-0.00951***	-0.00561***	-0.00906***	-0.0111***	-0.0116***
	(-7.85)	(-3.90)	(-5.10)	(-6.75)	(-5.82)
Constant	-0.205**	-0.246**	-0.715***	-0.362***	-0.722***
	(-2.99)	(-2.88)	(-8.05)	(-3.82)	(-6.85)
Observations	30587	20165	21445	20239	18808

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

For the examination for direct participation using Logit regression (see Table 9), we find stable and highly consistent results as for the total participation. More specifically, education has significant effect on the dependent variable, with an increase in the log-odds of the direct participation. A negative effect can be found from the employment, which is consistent with the study of Briggs et al. (2021) and Niu et al. (2020). Our results reveal that the employed household has higher possibility to participate in the stock market directly.

6.2. The impact of stock market participation on the wealth distribution

The results presented in Table 10 demonstrate the impact of stock market participation on the wealth distribution across five waves. The analysis focuses on the logarithmic form of the dependent variable, total household wealth, and examines the effects at the 25th quantile, median, and 75th quantile.

Consistently across the waves, the findings indicate that stock market participation significantly influences the wealth distribution. Specifically, when considering direct participation, the effects are more pronounced in the lower quantile compared to the higher quantile. For example, in Wave 1, a one-unit increase in direct participation leads to a 1.95% increase in total household wealth at the 25th quantile, whereas the effect is lower at 0.98% in the 75th quantile. These patterns persist across waves and quartiles. The observation that lower income groups exhibit higher responsiveness to direct participation can be attributed to two factors. Firstly, lower income households motivate to participate in financial markets to improve their financial situation, accumulate wealth, and seek investment opportunities that can potentially enhance their income or savings. However, the urgency of financial need can drive higher levels of responsiveness among the lower income group. Secondly, these households may be more sensitive to any changes in their financial circumstances. A change in income or wealth can have a relatively larger impact on their overall financial well-being compared to higher income individuals. As a result, lower income individuals may be more inclined to actively respond to opportunities for direct participation in financial markets to potentially improve their financial standing. Interestingly, the effect of indirect stock market participation (2.07%) is slightly higher than that of direct stock market participation (1.95%). This suggests that indirect participation has a slightly stronger impact on total household wealth. Moreover, the total participation effects surpass both direct and indirect participation. For the lower quartiles, the effects range around 2.21% across the five waves, while for the higher quartiles, the effects are approximately 1.10%.

When considering all five waves collectively, the results remain qualitatively consistent, further reinforcing the observed relationships between stock market participation and the wealth distribution.

Table 10: Quantile regression.

	Dependant variable: total household wealth														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
q25															
direct	1.203***			1.084***			1.207***			1.143***			1.123***		
	(32.48)			(45.69)			(36.68)			(32.85)			(56.35)		
indirect		1.286***			1.264***			1.400***			1.329***			1.322***	
		(43.01)			(47.85)			(40.81)			(40.81)			(49.79)	
participate			1.432***			1.380***			1.504***			1.442***			1.416***
			(58.75)			(42.19)			(46.85)			(47.88)			(47.50)
Age	0.558***	0.517***	0.495***	0.535***	0.472***	0.456***	0.549***	0.470***	0.448***	0.557***	0.474***	0.453***	0.0628***	0.0538***	0.0525***
	(41.08)	(39.20)	(42.17)	(55.59)	(37.66)	(42.16)	(50.01)	(38.46)	(36.73)	(49.33)	(43.30)	(38.00)	(43.15)	(39.44)	(33.19)
Education	-0.755***	-0.770***	-0.668***	-0.893***	-0.833***	-0.766***	-0.585***	-0.509***	-0.469***	-0.871***	-0.778***	-0.694***	-0.996***	-0.899***	-0.806***
	(-12.67)	(-14.90)	(-18.26)	(-21.47)	(-20.04)	(-21.17)	(-9.95)	(-8.12)	(-10.41)	(-14.56)	(-13.34)	(-16.21)	(-19.41)	(-14.19)	(-13.48)
Female	-0.512***	-0.556***	-0.489***	-0.464***	-0.475***	-0.427***	-0.465***	-0.461***	-0.382***	-0.504***	-0.527***	-0.463***	-0.469***	-0.524***	-0.440***
	(-19.77)	(-15.76)	(-17.40)	(-14.53)	(-17.46)	(-18.43)	(-15.66)	(-21.89)	(-14.14)	(-16.65)	(-17.41)	(-15.00)	(-12.39)	(-21.66)	(-16.70)
Employment	-0.605***	-0.625***	-0.563***	-0.519***	-0.525***	-0.463***	-0.535***	-0.518***	-0.460***	-0.493***	-0.495***	-0.437***	-0.495***	-0.500***	-0.457***
	(-25.24)	(-31.18)	(-23.72)	(-23.59)	(-20.19)	(-27.58)	(-24.33)	(-24.38)	(-21.08)	(-20.05)	(-23.68)	(-19.25)	(-23.55)	(-35.50)	(-19.63)
Socio-economic	-0.0152***	-0.0153***	-0.0144***	-0.0129***	-0.0132***	-0.0124***	-0.0135***	-0.0131***	-0.0124***	-0.0131***	-0.0131***	-0.0126***	-0.0158***	-0.0161***	-0.0152***
	(-11.95)	(-18.37)	(-16.93)	(-11.04)	(-9.82)	(-9.22)	(-19.30)	(-20.96)	(-11.62)	(-15.15)	(-20.09)	(-11.35)	(-13.71)	(-12.34)	(-13.67)
Constant	10.89***	11.22***	10.77***	11.08***	11.30***	10.92***	10.64***	10.80***	10.49***	10.98***	11.27***	10.91***	10.87***	11.23***	10.83***
	(144.04)	(138.30)	(173.97)	(140.09)	(151.42)	(175.44)	(128.09)	(142.76)	(135.55)	(120.82)	(129.42)	(168.18)	(101.31)	(123.43)	(113.80)

q50															
direct	0.860***			0.842***			0.919***			0.859***			0.849***		
	(44.84)			(46.32)			(34.71)			(52.86)			(52.14)		
indirect		0.924***			0.943***			1.031***			0.998***			0.992***	
		(44.43)			(62.80)			(50.29)			(54.97)			(59.48)	
participate			0.987***			0.995***			1.077***			1.037***			1.018***
			(58.55)			(48.55)			(53.23)			(49.76)			(42.53)
Age	0.476***	0.444***	0.434***	0.455***	0.421***	0.410***	0.473***	0.431***	0.423***	0.471***	0.417***	0.405***	0.0520***	0.0466***	0.0459***
	(63.46)	(45.14)	(49.86)	(48.30)	(32.63)	(40.91)	(65.19)	(41.51)	(42.05)	(44.05)	(37.20)	(49.12)	(41.87)	(35.75)	(35.18)
Education	-0.727***	-0.716***	-0.648***	-0.741***	-0.682***	-0.648***	-0.595***	-0.559***	-0.516***	-0.810***	-0.736***	-0.690***	-0.921***	-0.815***	-0.790***
	(-33.05)	(-32.34)	(-27.27)	(-22.57)	(-38.67)	(-31.98)	(-18.12)	(-16.63)	(-24.25)	(-27.34)	(-20.83)	(-27.91)	(-25.94)	(-24.53)	(-17.91)
Female	-0.372***	-0.414***	-0.360***	-0.379***	-0.383***	-0.356***	-0.356***	-0.361***	-0.319***	-0.387***	-0.409***	-0.353***	-0.371***	-0.383***	-0.353***
	(-21.86)	(-26.05)	(-24.61)	(-18.19)	(-22.12)	(-15.63)	(-20.03)	(-16.68)	(-19.42)	(-18.50)	(-19.19)	(-17.00)	(-19.75)	(-18.45)	(-24.18)
Employment	-0.424***	-0.449***	-0.412***	-0.369***	-0.414***	-0.372***	-0.385***	-0.420***	-0.388***	-0.345***	-0.375***	-0.333***	-0.385***	-0.411***	-0.385***
	(-33.65)	(-37.33)	(-26.37)	(-24.57)	(-18.59)	(-20.58)	(-33.19)	(-27.11)	(-20.76)	(-18.84)	(-19.84)	(-22.97)	(-21.35)	(-23.55)	(-20.04)
Socio-economic	-0.0128***	-0.0131***	-0.0125***	-0.0119***	-0.0111***	-0.0110***	-0.0136***	-0.0124***	-0.0120***	-0.0137***	-0.0133***	-0.0129***	-0.0151***	-0.0151***	-0.0145***
	(-14.74)	(-12.94)	(-19.04)	(-12.06)	(-9.83)	(-10.19)	(-17.78)	(-13.21)	(-14.18)	(-18.99)	(-15.68)	(-12.72)	(-12.97)	(-10.19)	(-11.85)
Constant	11.78***	12.03***	11.70***	11.83***	11.98***	11.74***	11.58***	11.74***	11.49***	11.90***	12.12***	11.85***	11.98***	12.14***	11.95***
	(273.39)	(300.47)	(231.13)	(363.97)	(210.83)	(201.12)	(197.55)	(215.21)	(238.32)	(196.49)	(245.50)	(270.16)	(213.11)	(193.90)	(303.17)

q75															
direct	0.758***			0.767***			0.823***			0.744***			0.694***		
	(45.87)			(43.45)			(44.73)			(38.45)			(37.90)		
indirect		0.819***			0.858***			0.930***			0.861***			0.830***	
		(35.32)			(50.33)			(44.35)			(44.37)			(39.98)	
participate			0.863***			0.902***			0.969***			0.909***			0.875***
			(48.83)			(46.64)			(83.44)			(39.06)			(52.47)
Age	0.387***	0.355***	0.350***	0.377***	0.339***	0.333***	0.396***	0.353***	0.344***	0.402***	0.359***	0.351***	0.0428***	0.0379***	0.0378***
	(47.23)	(50.76)	(49.95)	(43.67)	(32.49)	(36.17)	(35.42)	(38.74)	(31.49)	(49.83)	(29.78)	(37.12)	(27.46)	(28.39)	(25.32)
Education	-0.722***	-0.692***	-0.627***	-0.717***	-0.649***	-0.598***	-0.552***	-0.515***	-0.476***	-0.811***	-0.728***	-0.668***	-0.877***	-0.774***	-0.756***
	(-27.26)	(-39.14)	(-29.55)	(-36.62)	(-37.94)	(-25.10)	(-20.60)	(-18.80)	(-25.01)	(-38.20)	(-20.18)	(-25.93)	(-36.11)	(-27.71)	(-27.30)
Female	-0.321***	-0.332***	-0.306***	-0.305***	-0.309***	-0.293***	-0.272***	-0.293***	-0.268***	-0.307***	-0.313***	-0.291***	-0.301***	-0.299***	-0.274***
	(-19.89)	(-31.30)	(-20.96)	(-14.89)	(-17.59)	(-13.29)	(-19.21)	(-14.89)	(-14.97)	(-16.87)	(-18.24)	(-13.90)	(-11.91)	(-19.19)	(-16.35)
Employment	-0.279***	-0.317***	-0.281***	-0.241***	-0.285***	-0.252***	-0.262***	-0.312***	-0.282***	-0.232***	-0.282***	-0.250***	-0.258***	-0.299***	-0.287***
	(-30.77)	(-38.67)	(-28.27)	(-16.87)	(-18.29)	(-18.70)	(-18.32)	(-22.56)	(-13.61)	(-17.34)	(-17.00)	(-22.82)	(-14.58)	(-20.60)	(-13.69)
Socio-economic	-0.0078***	-0.0076***	-0.0071***	-0.0080***	-0.0077***	-0.0071***	-0.0095***	-0.0077***	-0.0079***	-0.0093***	-0.0092***	-0.0085***	-0.0088***	-0.0089***	-0.0082***
	(-10.71)	(-9.02)	(-8.78)	(-9.75)	(-13.44)	(-10.48)	(-8.84)	(-8.55)	(-6.96)	(-12.69)	(-11.60)	(-17.73)	(-8.75)	(-6.63)	(-9.14)
Constant	12.61***	12.81***	12.52***	12.56***	12.71***	12.45***	12.31***	12.52***	12.30***	12.67***	12.83***	12.58***	12.84***	12.97***	12.78***
	(289.41)	(359.23)	(293.43)	(282.42)	(194.43)	(255.56)	(188.73)	(218.88)	(338.80)	(322.35)	(306.77)	(263.54)	(202.60)	(172.72)	(224.94)
N	29129	29129	29129	19972	19972	19972	21195	21195	21195	20054	20054	20054	18618	18618	18618

The t statistics in parentheses;

*** Indicates statistical significance at the 0.1% level;

** Indicates statistical significance at the 1% level;

* Indicates statistical significance at the 5% level.

6.3. Robustness Check

In order to see effect of the treatment, the stock market participation, has been reduces or eliminates its impact by inclusion of the covariates. We run a robustness check by excluding controls, shown in Table 12 in the Appendix. Although the magnitudes for effects of different participation indicators increase significantly, the table reports a qualitatively consistent result with that in in Table 10.

7. Conclusion

This chapter focuses on examining the factors that influence stock market participation in the UK. The study utilizes a comprehensive dataset from the Wealth and Assets Survey to investigate the impact of various factors, including age, education, gender, employment, socio-economic status, and income, on individuals' decision to participate in the stock market. Furthermore, we explore how stock market participation affects the distribution of wealth in the UK.

The results are consistent with the theory and our expectation. Our results are consistent with previous studies and theories, comparing with those have no education qualification, those have education qualifications have higher in the log-odds of the dependent variable with different participation measures. Also, we find that the female tends to have less participated in the stock market. Moreover, the employment households are likely to participate into the stock market. Furthermore, we can see the higher income increase the participation in the stock market, either directly or indirectly.

When looking at the impact of the stock market participation on the wealth distribution, we find the impact is much higher in the lower quantile rather than in the higher quantile. This effect is stable across different waves. In detail, the total participation has the larger effect for the whole distribution. Our findings, however, also show that the effect of indirect stock market participation is slightly higher than that of direct stock market participation in all five waves. This is crucial to the policymakers that, as from our results, intervention in the stock market participation will affect the left tail more than the right tail. This might be one of the components of the wealth inequality in the UK. For further study, we will examine the importance of the stock market participation in explaining the wealth inequality in the UK, and in the US by using Survey of Consumer Finances (SCF).

Appendices

Table 11: Summary of Total household wealth between household across waves.

	Mean	Std. Dev.	Freq.
	Wave 1		
not participated	236891.03	471633.7	20,248
participated	809434.14	1152634.6	10,339
Total	430421.72	818323.2	30,587
	Wave 2		
not participated	236138.3	363069	12,125
participated	831234.8	1347007	8,040
Total	473409.6	942094.4	20,165
	Wave 3		
not participated	257467.2	390564.2	13,581
participated	879578.6	1067958	7,864
Total	485598.9	777618.5	21,445
	Wave 4		
not participated	300295.2	515304.4	12,833
participated	1027246	1887785	7,406
Total	566306.1	1262910	20,239
	Wave 5		
not participated	364572	681836.8	12,168
participated	1273381	5275552	6,640
Total	685419.1	3211559	18,808

Table 12: Quantile regression.

	Dependant variable: total household wealth														
	(Wave 1)			(Wave 2)			(Wave 3)			(Wave 4)			(Wave 5)		
q25															
direct	1.951***			1.835***			1.937***			1.919***			1.848***		
	(64.24)			(47.96)			(54.56)			(47.14)			(51.24)		
indirect		2.073***			2.057***			2.152***			2.164***			2.165***	
		(62.09)			(68.40)			(89.29)			(75.89)			(68.49)	
participate			2.209***			2.183***			2.246***			2.279***			2.229***
			(51.25)			(71.62)			(65.05)			(84.72)			(64.14)
constant	10.72***	10.72***	10.40***	10.90***	10.78***	10.49***	10.95***	10.75***	10.53***	11.06***	10.90***	10.65***	11.31***	11.10***	10.87***
	(439.01)	(384.52)	(261.87)	(316.18)	(451.37)	(389.13)	(358.88)	(495.36)	(408.24)	(330.63)	(329.69)	(440.46)	(433.19)	(330.51)	(322.08)
q50															
direct	1.174***			1.148***			1.185***			1.205***			1.167***		
	(78.23)			(52.33)			(65.50)			(53.54)			(55.46)		
indirect		1.272***			1.281***			1.331***			1.364***			1.340***	
		(66.61)			(62.86)			(94.51)			(90.58)			(73.40)	
participate			1.304***			1.329***			1.387***			1.432***			1.399***
			(82.38)			(63.64)			(75.42)			(79.55)			(85.30)
constant	12.11***	12.09***	11.91***	12.19***	12.10***	11.91***	12.28***	12.12***	11.97***	12.39***	12.26***	12.08***	12.59***	12.46***	12.29***
	(1194.42)	(1304.54)	(1207.61)	(1260.96)	(1180.80)	(976.62)	(978.13)	(1220.03)	(654.48)	(732.42)	(998.48)	(730.33)	(1123.18)	(1125.14)	(789.79)

q75															
direct	0.982***			0.966***			0.962***			0.940***			0.908***		
	(63.11)			(45.55)			(50.68)			(51.00)			(48.83)		
indirect		1.045***			1.092***			1.090***			1.095***			1.063***	
		(68.05)			(52.02)			(58.53)			(67.91)			(62.01)	
participate			1.110***			1.139***			1.151***			1.174***			1.109***
			(68.09)			(79.90)			(65.34)			(67.24)			(52.12)
constant	12.88***	12.86***	12.67***	12.92***	12.82***	12.66***	13.04***	12.89***	12.75***	13.19***	13.04***	12.87***	13.39***	13.24***	13.10***
	(1459.67)	(1733.30)	(1518.80)	(1215.35)	(1157.09)	(1210.43)	(1272.71)	(1294.88)	(888.62)	(941.95)	(1283.38)	(799.09)	(1247.46)	(1232.09)	(794.85)
N	29129	29129	29129	19972	19972	19972	21195	21195	21195	20054	20054	20054	18618	18618	18618

The t statistics in parentheses;

* Indicates statistical significance at the 10% level;

** Indicates statistical significance at the 5% level;

*** Indicates statistical significance at the 1% level.

Conclusions and Further Work

The chapter will provide a summary of each chapter. The second subsection discusses the implications of current thesis for investors, businesses, policymakers, etc. The third should discuss the limitations of this work and directions for future research.

Summary

This thesis consists of three separate chapters presented and discussed. This section offers a brief summary of the thesis and point out its implications and limitations that we can address and develop in our further study.

The Chapter 1 examines the main research hypothesis that the time zone would have negative impact on the M&A transaction cases in China, we answer the three research questions from this study: i) The Time Zone Difference positively associated with the time of M&A to be successfully implemented ii) The Time Zone Difference negatively impacts on the acquisition premium iii) The larger of Time Zone Differences increases the likelihood of paying method trading by stock instead of using cash payment. These research results highlight the negative effect of the Time Zone Difference in China due to the information asymmetry, this main finding contributes to the empirical confirmation of the importance of the information asymmetry in corporate mergers and acquisitions, also the other findings of this chapter have implications to the companies related to M&A, the acquirers would be able to earn relatively higher returns from the M&A transactions with the target company has lower Time Zone Difference compared to the one has higher Time Zone Difference.

The Chapter 2 contributes to the financial literature by suggesting the relationship between investor attention and covariance forecasting, Particularly, Google search volume index can be treated as a proxy to measure investor attention. Several studies link with GSVI and stock markets forecasting, which are almost focus on the stock variance analysis. To the best of my knowledge, this study is the first to examine the effect of Google search volume index on the covariance forecasting, which also involves the implied volatility data in order to possibly improve the forecasting performance. This study address three research questions as follows: i) Comparing the forecasting results with- and without- using GSVI, the empirical results highlight that the GSVI does contribute to the covariance forecasting ability for stock market. ii) Incorporating an incremental information of implied volatility with GSVI would even contribute more for covariance forecasting. iii) Comparing the predicating ability under the same context using the two multivariate models: random walk estimation and heterogeneous autoregressive model, a relatively better forecasting performance achieved with the heterogeneous autoregressive model.

The Chapter 3 analysed how the household stock market participation influence the wealth distribution in the UK. In the framework of the third study, we provide empirical evidence utilizing both probit regression and logit regression to test research hypotheses and get the following findings that are consistent with theories and our expectation: i) The household wealth level is positively related to the stock market participation. ii) As for the gender effect, we test the stock market participation rate of female is lower than that by male. iii) Stock market participation significantly affect the wealth distribution in the UK, especially the effect of indirect participation is higher than that by direct participation.

Implications

The results for Chapter 1 have significant and important implications in M&A transactions, hence the main implication of the findings is that Time Zone Differences should be taken into account. This study implies that Time Zone Differences are harmful to cross-border M&A. We further would like to suggest the managers to consider the time zone when they choose the targets in cross-border M&A integration.

In Chapter 2, we show that covariance forecasting serves several purposes for financial institutions predicating, which has potential benefits to help investors to conduct profitable investment strategies. Specifically, risk managers and equity analysts always use the covariance forecasts into value-at-risk models for inspecting by their central banks. A portfolio manager pay attention to assets covariance in order to create optimal portfolios. Considering covariance of underlying assets also helps option traders to price and hedge kinds of contingent claims, this study bridges the gap of covariance forecasting incorporating the consideration of investor attention by proxy using the GSVI.

Chapter 3 provides useful implications to both investors and policy makers by shedding more light on the factors and features of deciding on the household stock market participation, such as their gender, age, education, and income level, etc. Additionally, due to the household stock market participation can greatly affect the whole wealth distribution, which is a part of reasons to explain the wealth inequality in the UK, policy makers could consider this factor pursuing government policy towards tackling the wealth inequality and designing fairer development pathways.

Limitations and directions for future research

The research in the Chapter one could be extended in a number of dimensions, we investigate this study focused on China market only, as the fact that China is a developing country and the financial market is more mature in the US, so it is worthwhile to explore how does the Time Zone Difference matter to the US market? An interesting project could be considered may be based on the security data company (SDC) platinum database to explore the cross-border M&As in the US market.

The further potential project could be considered, for instance in Chapter two, the limited dataset used from 2007 to 2016 in that study due to the availability of purchased 5 min high-frequency data is until the end of the 2016. An intriguing domain for further study of the chapter two may be based on a larger covariance matrix for future study. Another prospective future research could further investigate whether the 5-min intraday data is the optimal frequency data to be intraday data using in covariance forecasting incorporating considering the investor attention?

One of the limitations in Chapter three is that the feature of data is cross sectional, we could not be able to identify any specific household cross waves by using the household ID provided. It would be worth to explore how the changes of stock market participation from different household could affect the whole wealth distribution. Another limitation is the uncertain applicability of this thesis to emerging markets, so the potential project is to examine other developing countries for the third study as the data used throughout this thesis mainly focuses on the UK market, but the emerging markets can be characterized by some different features and unique empirical evidence. I leave these extensions on the agenda for further work.

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