ROLE OF HIGH-FREQUENCY DATA, DISTRIBUTION ASSUMPTION AND TRADING VOLUME IN VOLATILITY FORECASTING IN CHINA STOCK MARKET

By

LIU MIN

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

November 2021

DEDICATION

To my family

for the time I had to spent away from you all …

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman : Associate Professor Choo Wei-Chong, PhD
Faculty : School of Business and Economics

Volatility forecasting has become a crucial process in risk management over recent decades. With the second largest stock market by market capitalization in 2019, China has gained increasing attention from recent research. This study aims at providing better volatility forecasts by investigating the role of high-frequency data, distribution assumption and trading volume in volatility forecasting based on the China stock market.

The behavior of high-frequency data in financial markets highly relates to market efficiency and information flow. The heterogeneous market hypothesis (HMH) is in response to the behavior of non-homogeneous market participants. In contrast to Efficient Market Hypothesis (EMH), HMH states that investors interpret information flow differently. Particularly, on a short-term basis, such as minute to minute, speculative behavior dominates the markets. In this regard, the study investigates the role of intraday data in volatility forecasting by using Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model. Besides, regarding the non-normal distribution of financial time series, a variety of distribution assumptions are incorporated in application. Furthermore, to examine the role of trading volume in volatility forecasting and test the validity of two conflicting hypotheses: the Mixture of Distribution Hypothesis (MDH) and the Sequential Information Arrival Hypothesis (SIH), trading volume is regarded as both long-run and short-run predictors by this research.

The considered methods contain the GARCH family model, the Heterogeneous Autoregressive (HAR) family model, the Smooth Transition Exponential Smoothing (STES), the Autoregressive Fractionally Integrated Moving Average (ARFIMA), and the GARCH-MIDAS model. In particular, in GARCH application, both intraday returns and daily returns are used and estimated under normal and non-normal distribution

assumptions. The contributions of this study are that: (1) it provides clear evidence to support that the superiority of traditional time series models in volatility forecasting remains by taking advantage of high-frequency data; (2) it incorporates different distribution assumptions in GARCH models to capture the stylized facts of high-frequency data; (3) it makes the first attempt to evaluate the performance of STES in volatility forecasting by using RV as the proxy of actual volatility; (4) it provides a more consistent comparison to evaluate the forecasting ability of a mixed data sampling approach; (5) it extends the literature on the forecasting performance of trading volume to the GARCH-MIDAS approach.

The empirical results show that: (1) data frequency in GARCH application substantially influence the accuracy of volatility forecasting, as the higher the frequency is of the return series, the better are the forecasts provided; (2) non-normal distributions are more capable at reproducing the stylized facts of both intraday and daily return series than normal distribution; (3) GARCH estimated by 5-min returns not only outperforms other GARCH alternatives, but also considerably beats RV-based models and STES at volatility forecasting; (4) no clear evidence appears that SIH holds in the China stock market; (5) GARCH-MIDAS is not able to beat the traditional GARCH method when both are estimated by the same predictors sampled at different frequencies.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PERANAN DATA BERFREKUENSI TINGGI, ANDAIAN TABURAN DAN VOLUM DAGANGAN DALAM RAMALAN VOLATILITI DI PASARAN SAHAM CHINA

Oleh

LIU MIN

November 2021

Pengerusi : Profesor Madya Choo Wei-Chong, PhD
Fakulti : Sekolah Peniagaan dan Ekonomi

Ramalan volatiliti telah menjadi proses penting dalam pengurusan risiko sejak beberapa dekad kebelakangan ini. Dengan pasaran saham kedua terbesar mengikut permodalan pasaran pada 2019, China telah mendapat perhatian yang semakin meningkat daripada penyelidikan terkini. Kajian ini bertujuan untuk menyediakan ramalan volatiliti yang lebih baik dengan menyiasat peranan data berfrekuensi tinggi, andaian taburan dan volum dagangan dalam ramalan volatiliti berdasarkan pasaran saham China.

Tingkah laku data berfrekuensi tinggi dalam pasaran kewangan sangat berkaitan rapat dengan kecekapan pasaran dan aliran maklumat. Hipotesis pasaran heterogen (HMH) adalah sebagai tindak balas kepada tingkah laku peserta pasaran yang tidak homogen. Berbeza dengan Hipotesis Pasaran Cekap (EMH), HMH menyatakan bahawa pelabur mentafsir aliran maklumat secara berbeza. Terutamanya, pada asas jangka pendek, seperti minit ke minit, tingkah laku spekulatif menguasai pasaran. Dalam hal ini, kajian menyiasat peranan data intrahari dalam ramalan volatiliti dengan menggunakan model Autoregresi bersyarat Heteroskedasticiti Umum (GARCH). Selain itu, mengenai taburan bukan normal siri masa kewangan, pelbagai andaian taburan dimasukkan dalam aplikasi. Tambahan pula, untuk mengkaji peranan volum dagangan dalam ramalan volatiliti dan menguji kesahihan dua hipotesis yang bercanggah: Campuran Hipotesis Taburan (MDH) dan Hipotesis Ketibaan Maklumat Berjujukan (SIH), volum dagangan dianggap sebagai peramal jangka panjang dan pendek dalam penyelidikan ini.

Kaedah yang dipertimbangkan terdiri daripada model keluarga GARCH, model keluarga Heterogenous Autoregresi (HAR), Eksponen Terlicin Alihan Lancar (STES), Autoregresi Percahan Integrasi Purata Bergerak (ARFIMA), dan model GARCH-MIDAS. Khususnya, dalam aplikasi GARCH, kedua-dua pulangan intrahari dan pulangan harian digunakan dan dianggarkan di bawah andaian taburan normal dan bukan

normal. Sumbangan kajian ini ialah: (1) ia memberikan bukti yang jelas untuk menyokong bahawa keunggulan model siri masa tradisional dalam ramalan volatiliti kekal dengan mengambil kesempatan daripada data berfrekuensi tinggi; (2) ia menggabungkan andaian taburan yang berlainan dalam model GARCH untuk menangkap fakta gaya data berfrekuensi tinggi; (3) ia membuat percubaan pertama untuk menilai prestasi STES dalam ramalan volatiliti dengan menggunakan RV sebagai proksi volatiliti sebenar; (4) ia menyediakan perbandingan yang lebih konsisten untuk menilai keupayaan ramalan pendekatan pensampelan data berlainan kekerapan; (5) ia melanjutkan literatur tentang prestasi ramalan volum dagangan kepada pendekatan GARCH-MIDAS.

Keputusan empirikal menunjukkan bahawa: (1) kekerapan data dalam aplikasi GARCH dengan ketara mempengaruhi ketepatan ramalan volatiliti, kerana semakin tinggi frekuensi siri pulangan, semakin baik ramalannya; (2) taburan bukan normal lebih berkebolehan untuk mengeluarkan semula fakta gaya bagi kedua-dua siri pulangan intraharian dan harian daripada taburan biasa; (3) GARCH dianggarkan dengan pulangan 5 minit bukan sahaja mengatasi alternatif GARCH lain, tetapi juga jauh lebih tepat daripada model berasaskan RV dan STES bagi ramalan volatiliti; (4) tiada bukti yang jelas bahawa SIH ditepati dalam pasaran saham China; (5) GARCH-MIDAS tidak dapat mengalahkan kaedah GARCH tradisional apabila kedua-duanya dianggar dengan menggunakan peramal yang sama yang disampel daripada frekuensi yang berlainan.

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This thesis was submitted to the Senate of the Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Choo Wei-Chong, PhD
Associate Professor
School of Business and Economics
Universiti Putra Malaysia
(Chairman)

Yee Choy Leong, PhD
Senior Lecturer
School of Business and Economics
Universiti Putra Malaysia
(Member)

Lau Wei Theng, PhD
Senior Lecturer
School of Business and Economics
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Professor and Dean
School of Graduate Studies
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Name of Chairman of Supervisory Committee:	Associate Professor Dr. Choo Wei-Chong
Signature:	
Name of Member of Supervisory Committee:	Dr. Yee Choy Leong
Signature:	
Name of Member of Supervisory Committee:	Dr. Lau Wei Theng

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller
APARCH	Asymmetric Power ARCH
ARCH	Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregression Fractional Integrated Moving Average
ARIMA	Autoregression Integrated Moving Average
ARMA	Autoregression Moving Average
CSRC	China Securities Regulatory Commission
DM	Diebold and Mariano
EGARCH	Exponential GARCH
EMH	Efficient Market Hypothesis
EPA	Equal Predictive Ability
ES	Exponential Smoothing
ESTGARCH	Exponential Smooth Transition GARCH
FIGARCH	Fractional Integrated GARCH
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
GDP	Gross Domestic Product
GED	Generalized Error Distribution
GJRGARCH	Glosten, Jagannathan and Runkle GARCH
HAR	Heterogeneous Autoregressive
HAR-J	HAR with Jumps
HAR-Q	HAR Quarticity
HARQ-J	HAR Quarticity with Jumps
HMAE	Heteroscedasticity Adjusted Mean Absolute Error

HMH	Heterogeneous Market Hypothesis
HMSE	Heteroscedasticity Adjusted Mean Square Error
IGARCH	Integrated GARCH
IPO	Initial Public Offering
JB	Jarque-Bera
LSTGARCH	Logistic Smooth Transition GARCH
MAE	Mean Absolute Error
MCS	Model Confidence Set
MDH	Mixture of Distribution Hypothesis
MIDAS	Mixed Data Sampling
MSCI	Morgan Stanley Capital International
MSE	Mean Squared Error
MZ	Mincer-Zarnowitz
ND	Normal Distribution
PP	Phillip-Perron unit root
QFII	Qualified Foreign Institutional Investor
QLIKE	Gaussian Quasi-likelihood
RQ	Realized Quarticity
RV	Realized Volatility
SGARCH	Standard GARCH
SIH	Sequential Information Arrival Hypothesis
SND	Skewed Normal Distribution
SPA	Superior Predictive Ability
SSE	Shanghai Stock Exchange

SSECI	Shanghai Stock Exchange Composite Index
SSM	Superior Set Models
STD	Skewed Student-t Distribution
STES	Smoothing Transition Exponential Smoothing
SZE	Shenzhen Stock Exchange
SZECI	Shenzhen Stock Exchange Component Index
TD	Student-t Distribution
YTD	Year-to-Date Return

CHAPTER 1

INTRODUCTION

1.1 Introduction

The considerable level of uncertainty in financial markets has brought forth increasing concerns on hedging risk especially after the financial crises in 1997 (Asia) and 2008 (global). Investment not only depends on profits that investors can get, but also the risks they may take during the investing period particularly in the stock market. As a widely used measurement of risk in financial markets, return volatility in recent decades has gained greater attention in regards to investment analysis, pricing of financial assets, and risk management. This study aims at providing more accurate volatility forecasts in the China stock market by evaluating the performance of a large number of competing models constructed from different frequencies.

As the leading emerging economy that possesses the world's second largest stock market, [1] China has announced a series of financial system reform policies to internationalize and deregulate its markets to accommodate the spread of globalization. Launched in the early 1990s and significantly dominated by individual investors who are more than likely irrational, speculation in the China stock market is sometimes comparable to gambling at a casino and regulations are needed to maintain the stability and well-behaved investment activities (see Su & Fleisher; 1998, Xu, 1999, Girardin & Liu, 2003, Mei et al., 2009, Lu et al., 2012, Lin et al., 2019, Xiao et al., 2021). Hence, some stylized facts that widely exist in return series such as the leverage effect are not observed in the scenario for China (see Narayan & Zheng, 2011). These characteristics lead to a large number of researches focusing on modelling and forecasting volatility in Chinese stock market in recent years (see Taylor & Sarno, 1999, Girardin & Joyeux, 2013, Liu et al., 2018, Li et al., 2019, Wei et al., 2020, Liu et al., 2021, among others).

A variety of methods have been introduced by previous researchers to capture the stylized facts of return series in past few decades and the number of methods is still steadily growing. Among them, Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models initially presented by Engle (1982) and extended by Bollerslev (1986) are most widely adopted in volatility modelling and forecasting. According to Bollerslev et.al (1992), GARCH-type models are the most successful and effective approach to capture the stylized facts of financial time series. The popularity and success of GARCH-type models is evidenced by considerable following literature focusing on theoretically extending GARCH-type models to various extensions as well

[1] Announced by the World Federation of Exchanges in 2019, https://www.world-exchanges.org/our-work/statistics

as empirical application in markets such as stock market, foreign exchange market, future market, bond market, oil market, etc.

However, the advent of high-frequency data has largely challenged the superiority GARCH-type models at volatility modelling and forecasting, because GARCH-type models are characterized as capable of capturing the stylized facts of daily or lower frequency return series. In particular, the introduction of realized volatility (RV) by Bollerslev & Andersen (1998) sheds new light on volatility forecasting. Computed from the aggregating intraday squared returns, RV is able to better reflect the information contained in trading hours and is less noisy than the daily close-to-close squared return. A large number of RV-based forecasting methods has been developed such as Autoregression Fractional Integrated Moving Average (ARFIMA) by Granger & Joyeux (1980) along with Hosking (1981) and Heterogeneous Autoregressive (HAR) of Corsi (2009). The outstanding performances of these methods are widely documented by recent literature (see Becker et al., 2007, Liu & Maheu, 2009, Konstantinidi et al., 2008, Asai et al., 2011, Lee, 2014, Patton & Sheppard, 2015, Tseng et al., 2015, Audrino & Knaus, 2016, Pu et al., 2016, Wang et al., 2017, Ma et al., 2019, Gkillas et al., 2020, Lehrer et al., 2021, Lyócsa & Stašek, 2021, Clements & Preve, 2021, Liu et al., 2022).

This gives rise to the issue of the role of high-frequency data in volatility forecasting. Particularly, how to improve the forecasting ability of traditional time series models in the light of increasing availability of high-frequency data. Will the superiority of traditional time series methods, especially GARCH-type models, could remain by incorporating information embedded in high-frequency data?

In response to above concerns, this research is dedicated to investigating the role of high-frequency data in volatility forecasting by conducting empirical research in the China stock market. Moreover, with regard to the non-normal distribution of return series and for the purpose of improving the forecasting accuracy, this research estimates GARCH-type models by incorporating different distribution assumptions to examine the role of distribution assumptions in volatility forecasting using GARCH-type models.

In addition, a variety of studies in the literature has emerged in recent decades to capture the feature of information flow that could significantly influence investment behavior and further determine the dynamics of financial time series. Among all alternatives, trading volume is widely regarded as one of the most notable proxies of information flow. For instance, Narayan et al. (2011) state that trading volume has statistically significant negative effects on price clustering in the Mexico stock market since it successfully captures market uncertainty. Baker & Stein (2004), Hong et al. (2006), and Girardin & Joyeux (2013) consider trading volume as the proxy for irrational investment and speculative activities. In general, the relationship between trading volume and volatility is among the center of recent researches (see Louhichi, 2011, Slim & Dahmene, 2016, Zheng et al., 2019, Liu et al., 2020, Kao et al., 2020, etc.).

However, there is in fact limited literature providing research on the role of trading volume in volatility forecasting in the China stock market. This research not only adds to the literature on the role of trading volume in volatility forecasting by taking the China stock market into consideration, more importantly, this research also extends the current research on the forecasting performance of trading volume to the Generalized Autoregressive Conditional Heteroscedasticity-Mixed Data Sampling (GARCH-MIDAS) approach. In this way, this research provides a more consistent comparison to evaluate the forecasting ability of the mixed data sampling approach as well as further investigate the role of data frequency in volatility forecasting.

In general, this research intends to examine the role of high-frequency data, distribution assumption and trading volume in volatility forecasting in the China stock market. The whole research is divided into two sub-studies. The first sub-study focuses on the role of high-frequency data and distribution assumption in volatility forecasting by comparing a large number of models including traditional GARCH estimated by daily return, intraday GARCH estimated by intraday high-frequency return, RV-based models including ARFIMA and HAR, and Smoothing Transition Exponential Smoothing (STES) proposed by Taylor (2004a) and Taylor (2004b). The second sub-study investigates the contribution of trading volume on improving the accuracy of volatility forecasting by adopting both GARCH-MIDAS approach and traditional GARCH-type models.

The remainder of this chapter runs as follows. Section 1.2 presents the background of the study. Section 1.3 presents the problem statement. Section 1.4 presents the study questions. Section 1.5 presents research objectives. Section 1.6 presents the significance of study. Section 1.7 briefly outlines the thesis. Section 1.8 concludes.

1.2 Background of the Study

Since the open and reform policy launched in 1978 by the Chinese government, China has undertaken a series of significant challenges to accommodate its economy to the trend of economic globalization and to boost its economic growth. After the gradual liberalization of its trade sector, property rights, foreign direct investment, and other major sectors of economy in past four decades, China has successfully emerged as the second largest economy in the world (see Chan et al., 2012, Xu et al., 2018).

However, being excessively protected by the government in long history, the liberalization of Chinese financial sector has turned to be one of the main controversial issue in transition its economy from government-regulated to market-oriented since China joined WTO in 2001. In the early 2018, Chinese president Xi Jing-Ping announced that the country would further open its financial sector by loosening the government restrictions on foreign access to Chinese insurance industry, the entry and expansion of foreign financial institutions, and improving the financial investment climate in general. More specifically, this includes a series of financial system reform including the liberalization of interest rates, internationalization of exchange rate, and the liberalization of capital account (see Petry & Petry, 2020).

Among these ongoing reform strategies, internationalization and deregulation of its stock market is one of the biggest challenges faced by Chinese authority. As the major financing and investment platform, stock market injects huge liquidity into economy and provides a crucial role in private sectors. However, a large amount of literature documents that Chinese stock market is not under well-behaved condition and has a long history of being dominated by highly speculative behavior and occasionally intervened by the Chinese authority (see Feng et al., 2021, Petry, 2021). To better understand the China stock market and facilitate our empirical research, this research presents a broad view for the historical development as well as the current situation of the China stock market as follows. It should be noted that this paper purely focuses on the China mainland stock market. Due to the "one country, two systems" policy, the Chinese Hongkong stock market is more internationalized and is not the scope of this research. Hence, for the remainder of the paper, the China stock market only refers to its mainland segment.

There are two stock exchanges in the China stock market: Shanghai Stock Exchange (SSE) located in Shanghai, and Shenzhen Stock Exchange (SZE) located in Shenzhen. SSE was formally established on December 19, 1990, and SZE on July 3, 1991. Both stock markets trade four hours a day from 9:30a.m. to 11:30a.m. in the morning and consecutively operate from 1:00p.m. to 3:00p.m. in the afternoon from Monday through Friday except the national holidays announced by Chinese government. Under controlled by China Securities Regulatory Commission (CSRC), SSE and SZE are not fully open to foreign investors and occasionally manipulated by the central government. The shares in both markets are divided into A shares and B shares. A share is only available to domestic investors and Qualified Foreign Institutional Investor (QFII). B share is available to both domestic and foreign investors. A share is priced in local currency and B share is priced in USD in SSE and HKD in SZE. As the major influential stock indices in China, SSE Composite Index (SSECI) and SZE Component Index (SZECI) are as a barometer for China's economy.

According to the report announced by World Federation of Exchange in 2019, SSE has been ranked at the fourth of largest stock exchange by market capitalization at US$4.02 trillion and SZE has been ranked at the eighth with US$2.50 trillion market capitalization. Meanwhile, with a total of US$6.52 market capitalization, the China stock market turns to be the second-largest stock market in the world with a total of 3639 listed companies' shares traded in the market (see Table 1.1).

Table 1.1 : Top 10 Stock Exchange by Market Capitalization

Stock Exchange	Jan. 1st.	July 14th.	YTD Performance	Market Cap.	No. of Companies
NYSE (USA)	11383.53	13210.91	16.05%	$22.90	3128
Nasdaq (USA)	6665.94	8161.79	22.44%	$10.08	3487
Tokyo (Japan)	19561.96	21534.35	10.08%	$5.67	3674
Shanghai (China)	2465.29	2937.11	19.14%	$4.02	1472
Hong Kong (China)	25130.35	28282.99	12.55%	$3.93	2365
Euronext	52.05	68.8	32.18%	$3.92	1208
London (UK)	6734.23	7541.69	11.99%	$3.76	2108
Shenzhen (China)	7259.49	9186.29	26.54%	$2.50	2167
Toronto (Canda)	14347.16	16541.99	15.30%	$2.10	1561
Boombay (India)	36254.57	38874.31	7.23%	$2.05	5461

Notes: YTD is the year-to-date return calculated by the subtraction of price on July 14th, 2019 and January 1st, 2019 divided by the price of initial date. It measures the performance of stock market during the calculation period. The second and third column indicates the price in each market. Market capitalization is measured in terms of trillion US$. The last column displays the number of listed companies in corresponding market. All data are obtained from World Federation of Exchange[2].

Figure 1.1 depicts the closing price of SSECI and SZECI from January of 2014 to September of 2019. Both indices are capitalization-weighted and indicate the historical performance of A share and B share listed on two exchanges. Noteworthy, Under the same driving forces, the dynamics of SSECI and SZECI are quite similar.

From Figure 1.1, it can observe two considerably volatile periods during 2007-2009 driven by global financial crisis and 2015-2016 driven by domestic excessive speculation. It is interesting to note that it only took less than two years to drive SSECI from the lowest point at 1011.5 in 2006 up to the historical high at 6092 in 2007, the price increased more than 6 times with an average growth of more than 300% per year during 2006-2007. However, it only took one year for SSECI to plunge to the second lowest point driven by global financial crisis in 2008.

The history repeated itself again in the middle June of 2015 with a three-week slump shaking off 30% Chinese share, more than 1400 companies filed for a trading halt in response to this unexpected huge drop and to avoid further losses. In an attempt to call a halt on further drop and stabilize the market, Chinese government poured considerable money into the market as an emergent rescue solution. Another slump occurred again on August 24th, 2015 after three-week peace, marking the largest fall since 2007 by 8.49% value lost in a single day.

[2] https://www.world-exchanges.org/our-work/statistics

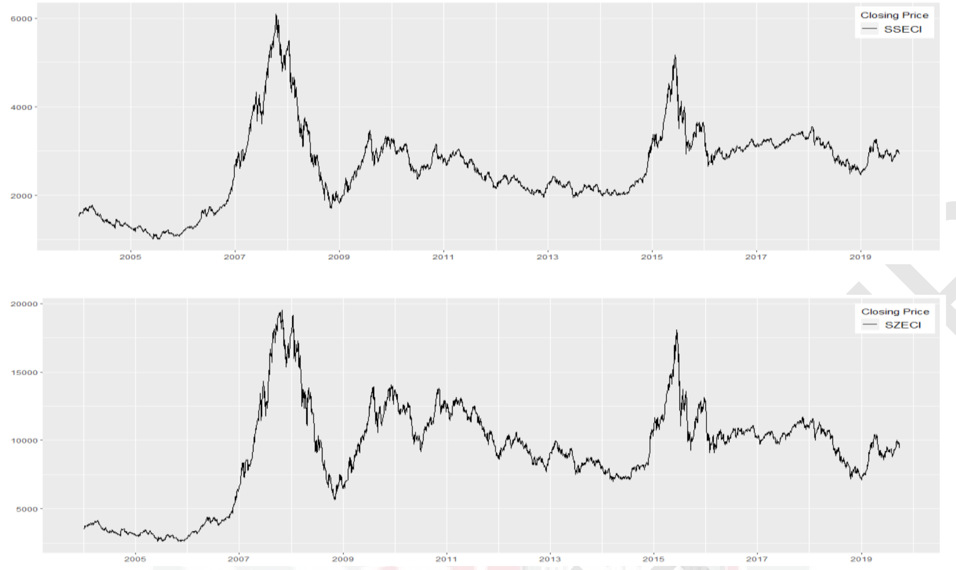

Figure 1.1 : Daily closing price of SSECI and SCZCI[3]

The lack of experience, inefficient regulation and uncontrollable fictitious transactions are the main reasons that lead the China stock market to be a highly speculative place. Dominated mainly by irrational and immature individual investors instead of relatively well-behaved institution since the establishment, Chinese authority has made huge efforts to gradually reshape its stock market to a well-behaved market. This research briefly overviews the historical events occurred in the China stock market in Table 1.2.

Among these events, some are characterized as milestones in opening the market. For instance, QFII program officially launched in 2002 allows the qualified foreign institutional investors to purchase A shares in local currency in SZE. These foreign investors consist of asset management companies, insurance companies, securities firms, commercial banks, and others such as pension funds, charity foundations, endowment funds, and sovereign wealth funds. QFII was initially administrated by distributing the limited quota to qualified institutions. Only qualified investors are allowed to invest in the China A share market. This limitation was officially terminated in 2019 in response to the intense trade war between China and US, as well as a major effort in pushing the opening-up Chinese financial market forward. The inclusion of A share in benchmark Emerging Markets Index by global index compiler Morgan Stanley Capital International (MSCI) in 2018 marks another milestone in the history of the China stock market.

[3] Data source: Shanghai Stock Exchange and Shenzhen Stock Exchange.

Table 1.2 : Major events in the history of the China stock market

Date	Events
1990	Launch of Shanghai Stock Exchange.
1991	Launch of Shenzhen Stock Exchange.
1992	Foundation of Chinese Securities Regulatory Commission (CSRC).
1994	Suspension of Initial Public Offering (IPOs) after 75% shares losses.
1996	10% daily limits adopted and ever since to avoid excessive speculation.
2001	Issuing rules to maintain market order as state-owned firms initially offered to public.
2002	Launch of Qualified Foreign Institutional Investor (QFII) program for foreign investors
2005	Elimination of non-tradable shares mostly state-owned or politically connected.
2005	IPOs suspended to avoid loss due to elimination of non-tradable shares plan.
2007	Trading taxes increased from 0.1% to 0.3% followed by a 21% price drop within 2 months
2007	Reaching the highest record of SSECI in history on October 16th at 6124.
2008	A 65% plunge due to the global financial crisis turns China to be the worst performer.
2008	Cutting the trading tax back to 0.1% on April 24th, 2008 to stabilize the market.
2008	IPOs suspended quietly on October.
2008	Two-year economic stimulus plan with 4 trillion Yuan injected to economy on October.
2009	The index gained 80% back in the year, IPOs resumed as market recovery from crisis.
2010	Implementation of the securities margin trading.
2015	30% value lost within three weeks, “Black Monday” on August 24th with 8.49% loss.
2016	An unsuccessful attempt to adopt circuit break to halt excessive market speculation.
2018	Inclusion of A share in benchmark Emerging Markets Index by global complier MSCI.
2018	Regarded as the worst performer in 2018 with 25% loss due to China-US trade war.
2019	Removing the quota limitation initially set to QFII to purchase A shares in China.
2020	Severely impacted by the COVID-19 Pandemic outbreak and contagion.

Some other efforts have been made to liberalize the market and create a level playing field for investors in the China stock market. For instance, before 2005, almost 70% shares in the China stock market were state-owned or owned by financial institutions which were literally governed by the center or local government. Starting from 2005, Chinese authority made huge efforts to eliminate the non-tradeable shares issued at the early stage of the establishment of stock market and initially held by state or politically connected institutional investors. An unstated contract between investors and regulators prevents the liquidation of non-tradable shares to protecting the interests of public investors.

Meanwhile, some experiences appear to be bitter memories in the history of the China stock market. For instance, on January 4th, 2016, Chinese authority adopted circuit breaks to prevent the excessive speculation activity and maintain the stability of the market. This attempt was found to be a huge failure and suspended only four days after the implementation with roughly 7% daily price drop both on the January 4th and 7th.

Although Chinese government has made considerable efforts to bridge the gap between Chinese stock market and the advanced, experienced stock market in developed countries by implementing a slew of boldly reform policies, it is still far from an efficient market as its financial development is still ongoing (see Girardin & Joyeux, 2013). Especially as long as the less informed and biased behavior of individual investors prevail in the market, the considerable level of uncertainty is still unavoidable (see Bailey et al., 2009). This can be witnessed by the unexpected acute volatility during 2015-2016. After almost 150% increasing from June 2014 to June 2015, the China stock market was characterized as heavily overvalued and the government constantly warned the investors to avoid the excessive risk exposure. According to Nicholas Lardy, once price falls even slightly it will result in a sharp market correction due to the market bubble and horrors among irrational individual investors[4]. These horrors eventually led the China stock market to recession after June 2015 until 2016 and resulted in considerable losses for the majority of market participants.

The rapid opening-up of domestic financial sector in quite recent years and the uncertainty of highly integrated global economy shed new light on Chinese stock market. It is now characterized as a market with considerable opportunities along with huge risks (see Lin, 2018, Lin et al., 2019). Therefore, volatility forecasting is getting more crucial for risk management, asset pricing, and investment portfolio in the China stock market.

1.3 Problem Statement

The ups and downs in the stock market is similar to roller coaster. This makes the stock market to be an attractive destination, especially for investors who has strong risk preference. Opportunity is always accompanied by risk in the stock market. In real investment, investors are more concerned about the fluctuation of price or the return of price which is actually the difference between the buying price and the selling price. Few investors pay attention to the fluctuation of returns which is essentially the volatility. However, ignoring the volatility of returns could induce a failure in investment. Normally, high return indicates high risk due to the fact that return is a compensation of taking risk. In this regard, to avoid excessive loss, investors are encouraged to acquire more knowledge about volatility. This is more urgent in China stock market regarding that the market is more volatile than that of developed country due to the fact that China stock market is mostly dominated by irrational individual investors rather than institutional investors. In this regard, along with relatively less efforts made to examine the dynamics of volatility in China stock market, this research makes attempts to add the literature in this strand. In this research, this research seeks to identify the superior methods which could provide accurate volatility forecasts in the China stock market. In particular, this research investigates the role of high-frequency data, distribution assumption and trading volume in volatility forecasting.

According to Andersen & Bollerslev (1998), actual volatility is unobservable. This presents the issue of properly measuring the actual volatility. In quite recent years, squared daily return is widely regarded as the measurement of actual volatility until the introduction of realized volatility (RV). The widely available high-frequency intraday data results in increasing attention shifting from traditional measurements of actual volatility, mostly based on daily returns, to RV constructed from intraday returns. Against this backdrop, a large amount of literature on RV estimation and forecasting has emerged for the past decades.

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[4] Nicholas Lardy, False Alarm on a Crisis in China, New York Times, 26 August 2015

However, the popularity of RV gives rise to the concerns on the performance of traditional volatility forecasting methods, especially the GARCH-type models which are well-known for the superiority in reproducing the volatility clustering feature of daily or lower frequency returns, rather than intraday returns. In addition to introducing RV-based models, a small number of researches have made efforts to improve the forecasting ability of traditional GARCH-type models by taking advantage of high-frequency data. For instance, Hol & Koopman (2002) and Zhou (2017) incorporate RV measures into the variance equation of GARCH model, but the results are discouraging. On the contrary, Fuertes et al. (2015) augment the GARCH model with RV as an incremental variable, showing a result that this augmentation leads to the largest forecasting accuracy gains. However, Jones (2003) demonstrates that the GARCH model is not able to reproduce the unconditional distribution of financial returns at frequencies higher than 24 hours.

Rather than incorporating the measures of RV to reflect the information contained in high-frequency data, a second strand in the literature substitutes daily return with intraday return and directly feeds intraday return into the GARCH model. This is inspired by Rahman et al. (2002) who point out that the distribution property of intraday return is similar with the daily return in the stock market and can be properly characterized by the GARCH model. However, no further evidence is provided by Rahman et al. (2002) with regard to the performance of GARCH model estimated by intraday returns (expressed as intraday GARCH for the remainder of this paper) in volatility forecasting. Chortareas et al. (2011) further investigate the forecasting ability of intraday GARCH using 15-min intraday return series in the foreign exchange market. The findings show that by incorporating high-frequency data rather than daily data into the traditional GARCH, the model's forecasting ability largely improves. Nevertheless, by fitting GARCH to intraday return series in the China commodity futures market, Jiang et al. (2017) state that no improvement is obtained and intraday GARCH is even worse than traditional GARCH in volatility forecasting.

Although limited researches pay attention to intraday GARCH in light of the increasing number of available RV-based models, the findings provided by Martens (2001) and Pong et al. (2004) with the statement that the higher the frequency of the return series is, the better are the out-of-sample volatility forecasts provided prompt us to apply intraday GARCH to the China stock market which has yet to be studied.

Another challenge posed by a GARCH application is the non-normally distributed properties of return series that are generally characterized as excess skewness, fat tail, and high peak. Neglecting these properties could draw misleading results according to Wilhelmsson (2006). Hamilton & Susmel (1994) are among the earliest to evaluate the performance of the GARCH model in volatility forecasting under different error distribution assumptions, followed by Chong et al. (1999), Lopez (2001), Wilhelmsson (2006), Shamiri & Isa (2009), and Dritsaki (2017), among others. A general consensus is that the GARCH model estimated under non-normal distribution provides more accurate forecasts than normal distribution since it is more capable of reproducing asymmetric and leptokurtotic stylized facts of return series.

There is in fact scant research providing evidence on the improvement of the GARCH model at volatility forecasting under different distribution assumptions in the China stock market. Su & Fleisher (1998) are the first to examine the stylized facts of return series in this market and estimate GARCH under normal and non-normal distribution assumptions. Although non-normal distribution outperforms in their research based on the output of the in-sample estimation, forecasting improvement is not discussed. More recent literature provided by Liu et al. (2009) and Zhou et al. (2019) evaluate the forecasting performance of the GARCH model under different distribution assumptions in the China stock market and suggest a non-normal distribution is superior to a normal distribution.

To enhance the forecasting ability of the intraday GARCH model, this research also takes a number of non-normal distribution assumptions into account in regard to the fact that the property of intraday return is consistent with daily return according to Antoniou et al.(1998) and Rahman et al. (2002). To the best of our knowledge, no study has yet to investigate the forecasting ability of intraday GARCH under different distribution assumptions in the China stock market.

The Mixture of Distribution Hypothesis (MDH) presented by Clark(1973) and the Sequential Information Arrival Hypothesis (SIH) introduced by Copeland (1976) and extended by Jennings et al. (1981) and Smirlock & Starks (1985) give rise to a strand of literature focusing on the relation between trading volume, one of the most notable proxies for information flow, and volatility. MDH suggests a strong, contemporaneous, and positive correlation between volume and volatility and is widely supported by the majority of studies in this field, such as Tauchen & Pitts (1983), Karpoff (1987), Andersen (1996), Chuang et al. (2009), and Chuang et al. (2012). However, with respect to the forecasting ability of trading volume, MDH states that trading volume is not able to provide further information which can improve the accuracy of volatility forecasting. On the contrary, SIH suggests that traders receive information in a sequential, random fashion and shift their demand curves accordingly. Equilibrium is reached once all traders have reacted to the information flow. Therefore, a lead-lag relation exists between trading volume and volatility.

Empirical research presents mixed results when testing SIH. After comparing 31 different statistical models and using squared return as the proxy for actual volatility, Brooks (1998) concludes that the predictive power of trading volume is negligible. Similarly, Kambouroudis & McMillan (2016) also support that the contribution of trading volume in volatility forecasting is insignificant. On the contrary, Chiang et al. (2010) re-examine the findings provided by Brooks(1998) and show that trading volume has strong predictive power on volatility forecasting if RV replaces squared return as the proxy of actual volatility. Consistent with Chiang et al. (2010), Tseng et al. (2015) also support SIH when investigating the volume-volatility nexus in the exchange traded fund market. The conflicting results highlight the importance of the measurement of actual volatility.

The arrival of GARCH-MIDAS introduced by Engle et al. (2009) and Engle et al. (2013) sheds new light on volatility modelling and forecasting by taking advantage of low frequency data as long-run component of volatility predictors. Typically, for a GARCH-MIDAS application, the short-run component of total conditional volatility is captured by the GARCH process. On the other hand, the long-run component of total conditional volatility is captured by Mixed Data Sampling (MIDAS) of Ghysels et al. (2004).

Asgharian et al. (2013) apply the GARCH-MIDAS approach to examine the importance of macroeconomic variables in volatility forecasting. Among all alternatives, GARCH-MIDAS with monthly RV outperforms the traditional GARCH. Pan & Liu (2018) extend GARCH-MIDAS to asymmetric GARCH-MIDAS and conclude that the asymmetric GARCH-MIDAS significantly improves upon the other competitors without considering the leverage effects. This is in line with the findings presented by Wang et al.(2020).

In fact, quite limited researches have focused on investigating the predictive power of the GARCH-MIDAS approach in contrast to the large number of studies pay attention to the in-sample estimation. Moreover, the existing literature evaluates the predictive ability of the GARCH-MIDAS approach by comparing GARCH-MIDAS that adopts a low frequency variable as its long-turn determinant to the traditional GARCH without combining the same variable due to unavailability of high frequency data. However, if the traditional GARCH is estimated by including the same variable that is adopted by GARCH-MIDAS but with higher frequency, one obtains a more consistent and reliable result.

In response to this concern, this research investigates the role of trading volume and data frequency by including monthly volume in the GARCH-MIDAS approach and also daily volume in traditional GARCH models. Hence, this research not only extends the current research on the forecasting performance of trading volume to the GARCH-MIDAS approach, but also provide a more consistent comparison to evaluate the forecasting ability of the mixed data sampling approach. Since the evaluation is based on different frequencies, this research further examines the role of data frequency in volatility forecasting.

1.4 Research Questions

The research questions of this research are as follows (also see Figure 1.2).

a) What are the roles of high-frequency data and distribution assumption in volatility forecasting?

To answer this question, this research further answers the following questions. 1) How do the high-frequency data influence the accuracy of volatility forecasting? 2) Which distribution assumption could better capture the stylized facts of high-frequency data? 3) How does the performance of intraday GARCH in volatility forecasting?

b) What is the role of trading volume in volatility forecasting?

To answer this question, this research further answers the following questions. 1) How does the trading volume influence the accuracy of volatility forecasting? 2) What is the performance of GARCH-MIDS approach in volatility forecasting?

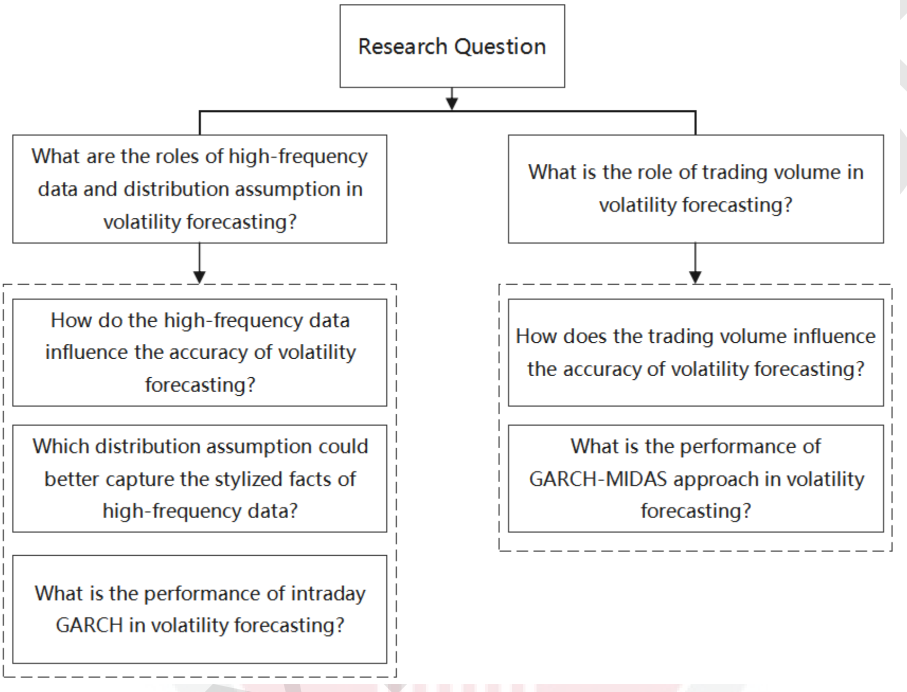

Figure 1.2 : Research questions of this research

1.5 Research Objectives

The general objective of this research is improving the accuracy of volatility forecasting in the China stock market. To achieve this objective, this research makes efforts to incorporate data with different frequencies and predictors into model estimation. In fact, improving the forecasting ability by model modification and using appropriate predictors are the main two strands in literature. Hence, the main objective is comprised of the following specific objectives (also see Figure 1.3).

a) To investigate the role of high-frequency data and distribution assumption in volatility forecasting.

This specific objective consists of three sub-objectives as follows. 1) To compare the performance of traditional GARCH to intraday GARCH. 2) To find out the best distribution to capture the stylized facts of high-frequency data. 3) To compare the performance of intraday GARCH to RV-based models.

b) To investigate the role of trading volume in volatility forecasting.

This specific objective consists of three sub-objectives as follows. 1) To extend the current research on the relation between trading volume and volatility to GARCH-MIDAS approach. 2) To compare the performance of GARCH-MIDAS approach to both traditional GARCH and intraday GARCH.

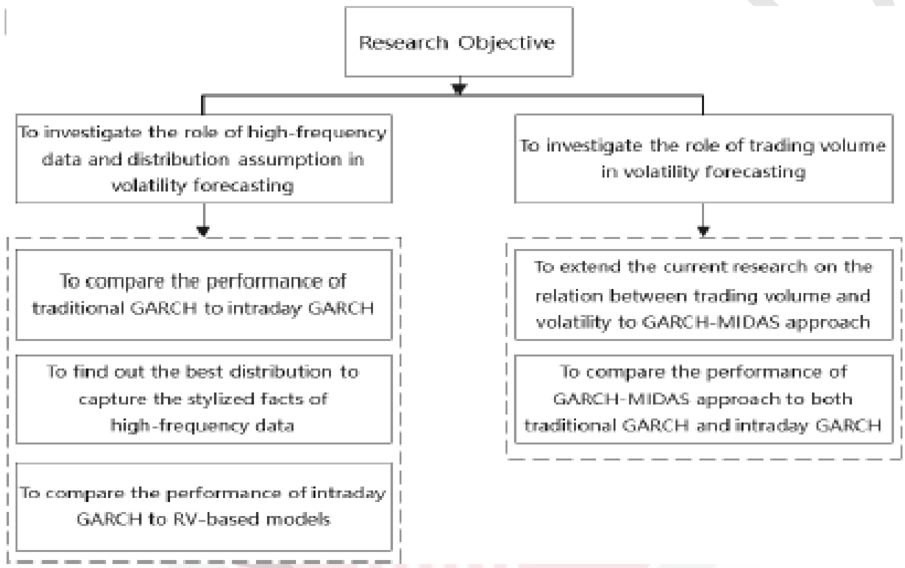

Figure 1.3 : Objectives of the research

1.6 Significance of Research

As the world second largest economy and the largest emerging economy, Chinese economic performance has been already under the world spotlight. Heavily dominated by the speculative investors, Chinese stock market presents its unique nature which makes the investment activity in Chinese stock market similar to gambling at a casino or riding the roller coaster. Although a series of reform and opening-up strategies have been undertaken and are still on the way, it is far away from efficient market. For instance, unexpected huge fluctuations can be observed from time to time. Ineffective regulations implemented by central government lead to the frequent occurrence of fictitious transactions, and the fake financial statements can be easily found from listed companies.

These situations implicate that seeking profits in Chinese stock market is quite risky and highlight the importance of capturing the dynamics of volatility in Chinese stock market to reduce the risk exposure. Especially during its financial sector transition period, Chinese stock market is widely regarded as a market with huge opportunities accompanied by huge risk. Hence, investigating the behavior of Chinese stock market volatility could facilitate participants to avoid losses resulted from the market fluctuation and has practical significance. Moreover, the findings of this research also facilitate participants as well as regulators of the other emerging economies whose stock market is also in the similar transition period.

Although there are enormous RV-based methods presented by literature to forecast volatility after the advent of RV in recent years, this research aims at investigating the performance of traditional volatility methods in volatility forecasting by incorporating high-frequency data and non-normal distribution assumptions. In other words, this research does not rule out the superiority of traditional time series method in the light of more and more RV-based methods available. On the contrary, this research intends to provide clear evidence to support that the traditional time series method could remain its superiority over RV-based methods in volatility forecasting by using high-frequency data as well as incorporating proper distribution to capture the stylized facts of financial series.

Another theoretical significance of this research is that this research tests the Heterogeneous Market Hypothesis (HMH) based on Chinese stock market. According to HMH, speculative behavior dominates the stock market on a short-term time basis. If the high-frequency data provide significant improvements on volatility forecasting in particular in Chinese stock market which is characterized as a market with highly speculative investors, HMH could not be rejected.

The long-lasting dispute on the contribution of trading volume to improving the accuracy of volatility forecasting is originated from two conflicting hypotheses known as the Mixture of Distribution Hypothesis (MDH) which rules out the possibility that trading volume could help to improve the accuracy of volatility forecasting and the Sequential Information Arrival Hypothesis (SIH) which supports that trading volume could contribute to improve the accuracy of volatility forecasting.

However, most existing researches on testing the validity of two hypotheses are focusing on the stock markets of developed countries. In this research, this research tests the above-mentioned hypotheses by using information from Chinese stock market. More importantly, this research extends the extant researches on the forecasting performance of trading volume to the GARCH-MIDAS approach. Moreover, considering the fact that the existing literature evaluates the predictive ability of the GARCH-MIDAS approach by comparing GARCH-MIDAS that adopts a low frequency variable as its long-turn determinant to the traditional GARCH without combining the same variable due to unavailability of high frequency data, this research provides a more consistent result by estimating traditional GARCH using the same variable that is adopted by GARCH-MIDAS but with higher frequency.

In this respect, this research looks to contribute to the literature by (1) providing clear evidence to support that the superiority of traditional time series models in volatility forecasting remains by taking advantage of high-frequency data compared with most of recent researches focusing on newly-arrived RV based model; (2) incorporating different distribution assumptions in GARCH model to capture the stylized facts of high-frequency data as no study has investigated the role of distribution assumption in intraday GARCH forecasting; (3) making the first attempt to evaluate the performance of STES in volatility forecasting by using daily RV as the proxy of actual volatility and applied to China stock market as previous study only focuses on weekly RV and developed countries in STES application; (4) providing a more consistent comparison to evaluate the forecasting ability of a mixed data sampling approach as previous study generally compares GARCH-MIDAS approach to traditional GARCH without predictor incorporated; (5) extending the literature on the forecasting performance of trading volume to the GARCH-MIDAS approach as previous study investigates the role of trading volume in volatility forecasting using data collected in same frequency; (6) presenting clear evidence to support that the forecasting ability strongly relies upon the data frequency as limited study makes comprehensive comparisons to reveal the role of frequency in intraday GARCH forecasting.

By doing this research, some useful information and valuable practical suggestions are provided to financial assets pricing, risk management, investment decision making. Meanwhile, the results could be applied to other financial market, such as future market and foreign exchange market, as well as the stock market of other countries especially those of emerging countries.

1.7 Outline of the Thesis

This research consists of five chapters. This research briefly outlines each chapter as follows.

Chapter 1 introduces the research by presenting research background of Chinese stock market, discussing the problem statement, describing the research questions, outlining the research objectives, and delivering the practical and theoretical significance of this research.

Chapter 2 reviews literature relevant to this research. This includes the concepts of volatility, the main stylized facts of return series, such as volatility clustering, leverage effects, and leptokurtosis, the measurements of actual volatility, the volatility estimation and forecasting methods adopted by this research, the relation between trading volume and volatility, and the literature gaps which this research intends to fill.

Chapter 3 describes the research design. To achieve the objectives of this research and fill the literature gaps, the research is organized as two sub-studies. This chapter also specifies the methodology adopted to conduct the research. This includes the estimation methods, the forecasting methods and the evaluation methods. This research also presents the data and preliminary analysis of the data. This includes the way this research constructs the actual volatility measurements.

Chapter 4 provides the result of the first sub-study which is the role of high-frequency data and distribution assumption in volatility forecasting in Chinese stock market. This includes the estimation results, forecasting results and evaluation results.

Chapter 5 provides the result of the second sub-study which is the role of trading volume in volatility forecasting in Chinese stock market. This includes the estimation results, forecasting results and evaluation results.

Chapter 6 concludes. This includes summary of findings, conclusion of empirical research, the contribution and implication of this research, and the suggestions for future study.

1.8 Summary of Chapter

This chapter is designed to introduce the background of the research, the research objectives, problem statement and the significance of the research. This research also briefly outlines the thesis.

This research first gives a brief introduction on theoretical and empirical development of studies regarding volatility modelling and forecasting in stock market. In order to better understand the characteristics of Chinese stock market, this research presents the historical development, important events or milestones, reform and open-up strategies, and the its current status in research background. Problem statement and study questions specify the problem of extant research and the questions this research intends to address. In this respect, this research presents general and specific objectives of this research. This research further discusses the practical and theoretical significance along with the expected contribution of this study. Lastly, this research briefly outlines the entire thesis.

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