An investigation of stock market volatility in Chinese stock markets and the effects of institutional investors

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Declaration

This thesis is the result of the author's original research. It has been composed by the author and has not been previously submitted for examination which has led to the award of a degree.

Signed: Date: Feb 19, 2020

Statement of Contribution of Co-Authors

Earlier versions of Chapter 2, 3, and 4 have been released for working papers. Chapter 3 and 4 are currently under editorial review. We aim to submit chapter 2 shortly after the viva. The undersigned hereby certify that:

1. they meet the criteria for co-authorship in that they have participated in the conception, execution, or interpretation, of at least that part of the working paper in their field of expertise;

2. they take public responsibility for their part of the publication, except for the responsible author who accepts overall responsibility for the working paper;

3. there are no other authors of the publication according to these criteria; and

4. there are no potential conflicts of interest that require to be disclosed to (a) granting bodies, (b) the editor or publisher of any journal or other publication.

In the case of Chapter 2, contributions to the work involved the following:

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Abstract

This thesis contributes to the literature on the investigation of stock market volatility in Chinese stock markets and the effects of institutional investors.

Chapter 2 focuses on the key characteristics of China's stock market that the volatility of stock returns tends to be greater, and to persist for longer, than is typical in 'western' markets. We provide persuasive arguments and evidence in support of the view that volatility persistence in part reflects the opacity of the information environment the majority of investors operate within. We go on to show that continuing reforms of state ownership and control, along with growth in the proportion of shares held by active institutional investors, look to be promising ways to mitigate the persistence in China's stock market volatility going forward.

Chapter 3 investigates the trading behaviour of institutional investors on extreme market movement days. Using daily cash flow data on the largest category of trades by value we construct a proxy for institutional trading and demonstrate that institutional trading behaviour consistently destabilizes both markets on extreme market movement days. We go on to highlight the conflating influence of regulator imposed daily limits to individual stocks' price movements. We conclude that binding price limits act to exacerbate the destabilising effects of institutional trading in Chinese stock markets.

Chapter 4 disaggregates the volatility of common stocks at the market, industry and firm levels by using daily stock return data of all listed firms in Chinese stock market. We find the time-series behaviour of idiosyncratic volatility in Chinese stock market is associated with large stock trading activities by institutional investors. Finally, we provide new evidence from industry-level study and show that much of the idiosyncratic volatility is concentrated in China's manufacturing industry, which is a leading indicator of the idiosyncratic volatility in other individual industries.

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Contents

List of Figures

List of Tables

Chapter 1

1. Introduction

Equity markets in China have expanded fast since the re-establishment of securities markets in Shanghai and Shenzhen in early 1990s. The two Chinese stock exchanges combined now constitute the second largest capital market in the world by total stock capitalization after the U.S., having surpassed Japan in 2014. Chinese stocks have become increasingly popular with global investors who are seeking benefits from international risk sharing and portfolio diversification. However, Chinese stock market has been documented to be more volatile than the other international stock markets (e.g. Wang *et al*., 2011; Li and Giles, 2015; Rizvi *et al*., 2018). The recent market crisis in 2015-2016 has further raised concerns amongst policymakers, regulators and global investors for the volatile feature of China's stock market where the daily trading volume is dominated by retail investors (Tian *et. al.* 2018).

As China's stock market has been growing rapidly with active steps toward financial revolution, this thesis aims to provide a comprehensive understanding of the sources and patterns of high volatility in China's stock market associated with trading behaviours of institutional investors from a modern perspective using firm-level data covered from 1998 to 2018. There are a series of key questions we address in the thesis: "What is sources of high volatility in China's stock market? What are the patterns of volatility dynamics? Which industry contributes to the highest volatility? What are the dynamic patterns across individual industries? Who contributes to the high volatility and who exacerbate the extreme market movement days, institutional investors or retail investors? Can price limit setup cool down the abnormal returns in market swings? Which factors impact the trading information environment in China's stock market."

This thesis aims to provide valuable insights for global investors who are seeking to benefit from international risk sharing and portfolio diversification, for active managers who are interested in home-biased equity allocation across individual industries in China's stock market, for financial regulators to identify the effectiveness of financial rules imposed in the stock market such as the price limit, and for researchers to have a better understanding the patterns in a typical emerging market given the results are noticeably different from those found in Western markets.

In order to investigate the volatility patterns and institutional trading behaviours in China's stock market, it is important to note that 'western' theories and concepts are not always applicable to China due to the difference in important regulatory issues or institutional environments, see for example Jiang and Kim (2015). Compared to the typical Western stock market, the first distinctive feature is that over 80%[1] of the daily trading volume in Chinese stock market is dominated by the retail investors who usually operate within an opaque information environment and are less rational in the investment strategy compared to institutional investors. Another unique characteristic is that many Chinese listed firms some form of government control, with limited disclosure requirements (e.g. Gul *et al.* 2010) or have been documented with poor performance compared to listed private firms (e.g. Chen *et al*. 2009). The statutory price limits imposed by China Securities Regulatory Commission is also an important factor in understanding Chinese stock market, in which the daily limits on price movements for regular and special treatment stocks are 10% and 5% respectively. The consequence of hitting the upper limit was that no further trades that would involve further upward price movements were permissible until the following (or subsequent) trading days. These distinctive features in Chinese stock market constitute the crucial components with regard to the research in Chinese stock market.

Considered for the distinctive features in China's stock market, the methodology adopted in this thesis not only draws from those established in the research of the typical Western stock market, but also incorporate the unique factors in China that are likely to impact the results. More specifically, when examining the trading information environment in Chapter 2, we take account of the evidence of substantial listed state-owned enterprises that are likely to operate in a more opaque information environment compared with private listed companies. In Chapter 3 when examining the abnormal returns of listed stocks in extreme market movement days, we incorporate the effect of price limit on the price movement in extreme days and extend the study to post extreme days to have a complete research on the price movement for substantial price-limit-hitting stocks. This is not an issue for the study on U.S. stock market (Dennis and Strickland, 2002) since there are no limits to daily stock price movements in use in the U.S. exchanges. Using the largest category of cash flow data, the institutional daily trading proxy we proposed in Chapter 3 and 4 is also based on the information of account holder by retail investors where most individual investors in China are not able to initiate the high-value trading documented in the largest category of cash flow data.

In brief summary, a fundamental theme of this thesis is to identify the volatility sources and institutional investors' trading behaviour while incorporating the distinctive characteristics in

[1] According to the trading data from Shanghai Stock Exchange from 2010 to 2017.

China's stock market so as to provide a better understanding for investors, policy markets and researchers on a fastly growing emerging market.

This thesis begins with Chapter 2, in which we examine the dynamics of volatility (i.e. volatility persistence) associated with trading information environment in China's stock markets and its potential drivers. We provide the empirical explanations of the evidence of high volatility persistence in China's stock market, which is associated with the factors related to the information environment such as ownership structure and uninformed trading by retail investors. Our study sheds light on the explanation of volatility persistence and also brings policy implication to financial regulators to alleviate the information asymmetry in China's stock market.

In this chapter, we first demonstrate that a distinctive characteristic of China's stock markets is that the volatility of stock returns tends to be greater, and to persist for longer, than is typical in 'western' markets. We first document this difference using data on the main stock price indices from Shanghai and Shenzhen markets, for Hong Kong, and for key US and UK indices over the period from 2010-2017 by employing autoregressive modelling of a range-based measure of volatility persistence. This finding is not new, see for example McMillan and Evans (2015) at the level of market indices, and Jain and Strobl (2017) who examine company level data. However, we are not aware of any literature that has so far evaluated potential explanations for this finding. This is the research gap that this chapter aims to address by exploiting an extensive company level dataset.

Built on the earlier theoretical study that suggested volatility persistence is associated with the trading information environment (Longin, 1997), we consider the compelling potential explanations for the persistence in the volatility of stock returns while incorporating the distinctive features in China's stock market that likely affect the findings such as ownership structures and institutional background. In particular, daily trading on the main Chinese stock exchanges is massively dominated by the trades of large numbers of individual (retail) investors, who operate within an opaque information environment, Piotroski, Wong, & Zhang (2015). Two features thought to be responsible for this relatively opaque environment are i) the fact that many Chinese listed companies are under some form of government control, with limited disclosure requirements, Gul, Kim & Qiu (2010); and ii) the fact that many Chinese listed companies have a single dominant shareholder, or sometimes a handful of shareholders, often government related, who hold a very large proportion of the company's shares, see Chen, Firth, & Xu, (2009). This structure is likely to inhibit the operation of a channel by which shareholders might (in more mature markets) be able to exert collective pressure on information disclosure.

We are able to demonstrate that the persistence in firm level stock price volatility is positively associated with ownership concentration (having controlled for firm size, book to market ratio, turnover ratio, and year and industry effects) and is highest when the largest shareholder is local government related. Therefore, the finding suggests the unique ownership structure of listed companies in China's stock market partly contributes to the higher volatility persistence compared with typical Western market. We go on to assess whether moves aimed at improving the information environment by China's financial regulators in recent years have had any significant impact on volatility persistence. In particular we look at i) the role played by growing numbers of financial analysts in China's stock market, see related discussions in Chan & Hameed (2006), Feng, Hu & Johansson (2016), and China, Li, Lu & Ling Lo (in press); and ii) attempts to increase the ownership of institutional investors (see, for example, Boone & White, 2015; Lin & Fu, 2017).

Our results indicate that the growth and coverage of analyst reports has significantly reduced volatility persistence in the Chinese stock market, and this reduction is more marked in the case of State-Owned Enterprises where the largest shareholder is government related. Further, the growth in institutional investment from mutual funds and continuing reform of state ownership/control look to be promising ways to mitigate the persistence of volatility going forward.

The fundamental contributions made by this chapter are i) to take the first attempt to fill the research gap on the potential explanations of volatility persistence using firm-level data in China's stock market and provide new evidence that the persistence in the volatility of stock returns is associated the opaque information environment such as high ownership concentration and dominated retail trading; and ii) we provide policy implications that the growth in the quantity of company specific analyst reports and active institutional investors in recent years is helpful to alleviate the information environment in China's stock market.

Chapter 3 pays particular concern on the extreme market movement days given understanding the source of market swings in recent market crash of Chinese stock market has aroused much attention of investors and researchers (Tian *et al*., 2018). This chapter aims to examine whether the trading activity by institutional investors or retail investors drives to the extreme market movements in China's stock market, and whether the price limit rule imposed helps to stabilize the abnormal return. Understanding these two questions benefits the investors a better understanding of the patterns of underlying risks in Chinese stock market, also provides insights to financial regulators on examining the roles of price limit rules played in these days.

Our first contribution of this chapter is to propose a more appropriate proxy for daily institutional investors' trading based on the existing related literature. In order to identify the sources of extreme swings in stock prices, two prior studies are key: Dennis and Strickland (2002) and Tian *et al.* (2018). Both these studies use institutional ownership data as a proxy that is intended to capture the influence of institutional traders. One disadvantage of these ownership data is that they are only available on a quarterly basis, while the extreme market movements are captured on a daily basis.

In our view, quarterly data on institutional holdings of each firm's stock is too restrictive and imprecise to proxy the influence of institutional traders on extreme market movement days (several of which sometimes occur within a given quarter); we suggest that use of his proxy is likely to conceal important details about the shorter-term activities of the traders in question. As suggested, albeit in different contexts, by Campbell, et al. (2009) and Boehmer and Kelley (2009) among others, we argue that it is vital to seek an alternative, higher frequency, proxy for institutional trading in order to have a better chance of explaining whether institutional trading plays a role in generating and/or prolonging extreme market swings.

In our study we exploit available daily cash flow data relating to individual firms' stocks to construct a more appropriate proxy for the daily trading activities of institutions. Our proposed proxy relies on daily cash flow data on transactions by value, obtained from the RESSET database. From these data we focus purely on those transactions on a given trading day that have a value in excess of one million Chinese RMB, i.e. the largest category of transactions that has consistently been recorded in the database over our sample period.

Using our proposed proxy by daily cash flow data to capture the trading behaviour of institutional investors, we consistently find that institutional investors destabilize the extreme market movement days, which contrast with those in Tian et al. (op cit.), suggesting that the quarterly proxy used in this prior research does not incorporate the necessary level of detail required to capture the impacts of daily institutional trading behaviours.

Our chapter also adds value to the existing literature on extreme market movement days in China's stock market (Tian et al. (op cit.)) by incorporating the effect of price limit effect on the study. We argue that it is essential for a complete analysis of the impacts of institutional trading to incorporate information on price movements that occur on days subsequent to days when the price limits are hit. In our analysis of individual firms' stock returns on the days following extreme market movement days, we find that: when stocks hit upper (lower) price limits their price continues to increase (decrease) for at least two further days; Finally, we show that net institutional sales on extreme days are significant predictors of subsequent abnormal returns. Therefore. we conclude that binding price limits act to exacerbate the destabilizing effects of institutional trading in Chinese stock markets.

Overall, a key innovation in this chapter is to improve on existing studies that have relied on quarterly data to proxy for the influence of institutional investors by constructing and using a new proxy that uses daily cash flow records on large transactions by value to better capture the daily trading activity of institutional investors. Based on this, a fundamental contribution is that we identify the destabilizing effect of institutional trading in China's stock market with price limit rule imposed both on and after extreme market movements. Our findings also provide policy implications of the destabilizing role played by price limit rules in market swings, which also are supportive of the active steps the regulators are undertaking towards the financial liberalization of price limits such as the launch of Shanghai's Star Market at July 22, 2019.

Chapter 4 takes the first attempt to decompose the aggregate volatility into market, industry and firm in Chinese stock market using daily stock return data of all listed firms in Chinese stock market from 1998 to 2018. This chapter sheds light on the dynamic patterns of volatility components at market, industry and firm-level in China's stock market, and thereby pay particular attention to idiosyncratic volatility that of the key interests of investors for portfolio diversification. Although the idiosyncratic volatility in Chinese stock market has aroused much attention recently (See Wan, 2018, Gu *et al.*, 2018, Xie *et al.*, 2019 and Gu *et al.*, 2019 among others), there are a lot of unexplored questions: "who drives to idiosyncratic volatility in China's stock market? Which industry contributes the largest part of aggregated idiosyncratic volatility? What is the dynamic patterns of idiosyncratic volatility across industries?"

As China's stock market has been growing rapidly in recent years, understanding the source of volatility and the patterns of idiosyncratic volatility become an undoubtedly important issue for global investors who seek for portfolio diversification in international of industrial levels, and for financial regulators to identify the pattern of risks in Chinese stock market.

In order to identify and study the source of the volatility in the U.S. stock market, Campbell, Lettau, Malkiel and Xu (hereafter CLMX, 2001) are the first topropose a volatility decomposition approach which disaggregates the volatility of common stocks into the market, industry and idiosyncratic components. The volatility decomposition approach of CLMX enables a clean disaggregation of total return volatility into market, industry and idiosyncratic components. Using this volatility decomposition approach, a number of studies extend the research in U.S. stock market to examine the relation between the decomposed volatility and trading activity of retail investor (Brandt et al., 2010) or the volatility patterns across individual industries (Wang, 2010).

Although volatility decomposition in U.S. stock markets has been well established, much less attention has been drawn to the Chinese stock market. This chapter aims to fill this research gap to investigate the patterns of volatility at market, industry and firm-level by using CLMX volatility decomposition approach.

By adapting CLMX approach into China's stock market, our first contribution is to identify whether there is an increasing trend of idiosyncratic volatility, as the increased idiosyncratic volatility is beneficial for portfolio diversification for investors (Campbell et al., 2001). We do not find any trend of idiosyncratic volatility in our investigation period. Instead, idiosyncratic volatility is characterised by an autoregressive process with regime shifts associated with financial crisis periods.

Our second contribution is to investigate an unexplored question of whether the trading activity of institutional investors or retail investors is responsible for the time-series behaviour of idiosyncratic volatility in China's stock market. Following Darby *et al.* (2019), we use the cash flow data from the largest trading group as the proxy for institutional trading, and find that idiosyncratic volatility is significantly associated with high stock price and trading activities of institutional investors. Our results contrast the findings of Brandt *et al.* (2010) in U.S. stock market and the conjecture of Nartea *et al.* (2013) in Chinese stock market. Furthermore, the results are also robust when using other measures of idiosyncratic volatility such as CAPM and Fama-French three factors models.

We go on to investigate the idiosyncratic volatility patterns in individual industries, as industry allocation is an increasingly important consideration for active institutional investors (e.g. Cavaglia et al., 2000, Carrieri et al., 2004). We first present the evidence of no long-term trend for each of the largest 15 industries in Chinese stock markets, reflecting the fact that the no trend evidence of aggregate volatility is not due to the trade-off effect of mixed upward and downward trends across industries. We then provide new evidence from industry-level study and show that much of the idiosyncratic volatility is concentrated in China's manufacturing industry, which is a leading indicator of the idiosyncratic volatility in other individual industries. The results contained in this industry level study provide implications for investors who consider home-biased equity allocation policies.

The fundamental contribution of Chapter 4 is to provide a comprehensive review of the volatility patterns at market, industry and firm levels by using a volatility decomposition approach. It is hoped the results contained in Chapter 4 provide implications for investors on portfolio diversification at both international and home-biased level, and for financial regulators to understand better for the underlying risks in China's stock market.

The thesis developed by these chapters is therefore centered on the theme of stock return volatility and institutional trading behaviour in Chinese stock market while incorporating the unique features of China's stock market. As such, the results contained in the thesis are largely different from those of study on typical Western stock markets. We hope the thesis will help to bring a better understanding of a rapidly growing emerging market for researchers, investors, and financial regulators.

Chapter 2

2. On the Drivers of Persistence in Stock Market Volatility in China

2.1 Introduction

In this chapter we demonstrate that a distinctive characteristic of China's stock market is that volatility tends to be greater, and to persist for longer, than is typical in 'western' markets. This chapter provides the empirical explanation that the evidence of high volatility persistence in China's stock market is associated with the factors related to the information environment such as ownership structure and uninformed trading by retail investors. To the best of our knowledge, this chapter takes the first attempt to both document and evaluate a number of potential explanations for high volatility persistence in China's stock markets using company level data. Our study sheds light on the explanation of volatility persistence and also brings policy implication to financial regulators to alleviate the information asymmetry in China's stock market.

In this study, we start with providing the evidence of high volatility persistence in China's stock market using data on the main stock price indices from Shanghai and Shenzhen markets, and for key US and UK indices over the period from 2010-2017. We then go on to document volatility persistence in company level data. Our main daily dataset spans all companies listed on the Shanghai or Shenzhen stock exchanges over the years 2010-2017 and is compiled from China's Stock Market and Accounting Research (CSMAR) database.

In considering compelling potential explanations for the persistence in the volatility of stock returns it is important to note that 'western' theories and concepts are not always applicable to China, see for example Jiang and Kim (2015). In particular, daily trading on the main Chinese stock exchanges is massively dominated by trades made by large numbers of individual (retail) investors, who operate within an opaque information environment, as discussed in Piotroski, Wong, and Zhang (2015). Two features thought to be responsible for this relatively opaque environment are i) the fact that many Chinese listed companies are under some form of government control (McMillian and Evens, 2015), with limited disclosure requirements, as noted in Gul, Kim and Qiu (2010); and ii) the fact that many Chinese listed companies have a single dominant shareholder, often government related, or sometimes a handful of shareholders, who hold a very large proportion of the firm's shares, see for example

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An earlier version of this chapter has benefited from the comments on presentation at Annual Conference of the Scottish Economic Society in April 7-9, 2019.

Chen, Firth, and Xu, (2009). This kind of ownership structure is likely to inhibit the operation of channels through which shareholders would, in more mature financial markets, exert collective pressure on information disclosure.

We are able to demonstrate that the persistence in firm level stock price volatility is positively associated with ownership concentration (having controlled for standard firm size, book to market ratio, turnover ratio, industry and year effects) and is highest when the largest shareholder is local government related.

In order to examine the factors that are helpful to alleviate the information asymmetry, we go on to assess whether moves aimed at improving the information environment have had any significant impact on volatility persistence. In particular we look at i) the role played by growing numbers of financial analysts reporting on China's stock market, motivated by related discussions in Chan and Hameed (2006), Feng, Hu and Johansson (2016), and Li, Lu and Ling Lo (2019); and ii) the Chinese government's moves toward increasing institutional ownership of shares, when active institutions are large shareholders they should be able to monitor companies they invest in, reducing information asymmetries, reducing agency problems and maximizing shareholder value by virtue of their superior skills, resources and more sophisticated processing of information, see Ajinkya, Bhojraj and Sengupta (2005), Boone and White (2015), Firth, Gao, Shen and Zhang (2016), Lin and Fu (2017) and Li, Rhee and Wang (2017).

Our study contributes to the literature in several ways. First, we take the first attempt to fill the research gap on the potential explanations of volatility persistence using firm-level data. Second, we supplement existing research on Chinese stock market dynamics by providing new evidence that the persistence in the volatility of stock returns is associated the opaque information environment such as high ownership concentration and dominated retail trading. Third, we add to the existing literature that examine information opacity in stock markets and provide the first such study assessing whether growth in the quantity of company specific analyst reports and in the prevalence of various types of institutional investors has had any impact on company level volatility persistence.

To briefly preview some of our key results to provide policy implication for financial regulators, we demonstrate that growth in analyst coverage has significantly reduced volatility persistence in the Chinese stock market, and that this reduction is more marked in the case of State Owned Enterprises where the largest shareholder is government related, consistent with these being the companies with the biggest scope for improvement in information disclosure. We also find evidence to suggest that some categories of institutional investors, mutual funds in particular, have had a discernible effect of reducing volatility persistence, alleviating the information asymmetry in China's stock market.

2.2 Literature Review

The empirical results of more than three decades in financial market point toward the conclusion that volatility of stock prices changes in a persistent manner. However, the focus on the comparison and explanation of volatility persistence has aroused far less attention. One of the reasons is that majority of prior research in modelling volatility has applied GARCH model, proposed by Bollerslev (1986), and its extensions. A number of studies have pointed out that GARCH-types models have put too much persistence in modelling volatility (e.g. Hsieh, 1993; Chou et al, 2015), leading less discernible difference of volatility persistence observed among assets.

Using an alternative realized volatility approach, the research by McMillian and Evans (2015) is one of the few studies that compare the difference of volatility persistence among asset groups. They examine the nature of equity ownership of state-owned enterprises (SOEs) for over 2,000 listed firms in China from 1991 to 2011. By the construction of monthly realized volatility calculated from the sum of squared daily stock returns, they find that the degree of volatility persistence of SOEs is higher than that of non-SOEs. However, there are key questions that are still not discussed in this literature that i) why the degree of volatility persistence of SOEs is higher than non-SOEs in China's stock market; and ii) the drivers to volatility persistence in China's stock market. As far as we know, no previous research has investigated the drivers of volatility persistence in stock markets. Nevertheless, an early theoretical study by Longin (1997) suggests that the degree of volatility persistence depends on the number of informed investors. As such, the factors associated with the information environment of trading are promising to explain our researcher question of the drivers of volatility persistence in China's stock market.

With respects to the potential explanations for the persistence in the volatility of stock returns in China's stock market, Jiang and Kim (2015) provide a modern overview of corporate governance in China and argue that using Western financial theory to study China may be simply outdated. In particular, two distinctive features in Chinese stock market are likely to contribute to the opaque information environment, of which are the ownership structure with a substantial amount listed SOEs (e.g. McMillian and Evans, 2015) and dominated trading volume by retail investors (Li and Wong, 2010).

Previous studies have shown the information environment is associated with the ownership structure of listed companies in Chinese stock market. Using firm-level data over the 1996-

2003 period, Gul et al. (2010) investigate the effects of the largest-shareholder ownership concentration on the process of firm-specific information incorporated into the stock price, as proxied by synchronicity. They find the entrenchment effect of ownership concentration significantly increase synchronicity and impedes the incorporation of firm-specific information into share prices, the effect of which becomes strong the largest-shareholder is government-related. Feng et al. (2016) extend this study to examine the effects of ultimate ownership structure on stock return synchronicity in China's stock market from 2005 to 2012, and argue that controlling owners have an incentive to limit firm transparency, leading to the more opaque information environment. Another study by Chen et al. (2009) groups China's listed companies into those controlled by SOEs affiliated to central and local government to investigate the difference of firm performance across various types of controlling shareholders. They find that the firm performance of central SOEs are better than local SOEs subjecting the strict monitoring by the State-owned Assets Supervision and Administration Commission. Although the effect of ownership structure and nature on information environments such as stock synchronicity has been examined, the related effect on volatility persistence in China's stock market remains an unexplored question.

A number of other factors have been also documented to impact the information environment in China's stock market. For example, Lin and Fu (2017) focus on the influence of institutional ownership influence on firm performance, and find positive effects of active institutional investors (mutual funds and international investors) on firm performance under active monitoring view in China's stock market. Du, Li and Ouyang (2013) look into the impact of foreign institutional ownership on Chinese stock return volatility, but do not look into any of these potential impacts on volatility persistence. Apart from the effects of institutional ownership, Feng et al. (2016) find analysis reports in China's stock market play an important role to facilitate market-level information dissemination and reduce information asymmetry, especially for firms with complicated ownership. Despite these existing literature have investigated the effects of institutional ownership and analyst coverage on the information environment, the related impacts on volatility persistence have reached few attention.

In summary, this chapter aims to fill the research gap of the drivers of volatility persistence in Chinese stock market that are associated with the influence on the information environment documented in the literature.

2.3 Data

Our initial analysis of volatility and volatility persistence employs daily data for the Shanghai and Shenzhen composite indices. We supplement these data equivalent indices covering key

US and UK indices from Bloomberg. More specifically, the US indices in our analysis include S&P 500, Dow Jones Industrial Average, and Nasdaq composite indices, whereas the FTSE100 and FTSE all-share indices are included in UK indices.

The dataset employed in our core analysis of the Chinese markets consists of daily high, low, opening and closing prices of shares of every company listed on either the Shanghai or Shenzhen stock exchanges from the first day of trading in January 2010 to the final day of trading in December 2017. These data were obtained from the China Stock Market and Accounting Research (CSMAR) databases.

We also use the CSMAR database to obtain annual data for each listed company on turnover rates (i.e. trading volume as a proportion of the number of shares outstanding), market capitalization, book to market ratios, and to construct an indicator of the percentage of shares held by the largest single shareholder. We also define a dummy variables for state ownership (SOE=1 if the largest shareholder is government-related, =0 otherwise), and a dummy for Central Government Ownership, CSOE, and another for Local Government Ownership, LSOE, such that SOE=CSOE-LSOE.

We supplement these data with information from the Wind Financial Database on institutional ownership. Specifically we identify the proportion of each company's shares held by institutional investors and are able to disaggregate institutional ownership into two groups: active and passive institutional owners, as suggested by Lin and Fu (2017), or into the finest four part disaggregation available in the database: i) mutual funds; ii) qualified foreign institutional investors (QFII), iii) other non-state owned financial institutions (a category that combines holdings including securities, insurance, pension and trust firms) and iv) 'other' institutional investors (a category that combines holdings of state-owned banks and asset management organizations, universities, government agencies, labour unions and research institutions).

2.4 Volatility and volatility persistence

We begin by presenting international evidence on stock market volatility and volatility persistence, employing three complementary estimates over the period January 2010-December 2017. The first set of measures draw on McMillan and Evans (2015) who made cross country comparisons of monthly volatility of stock returns, expressed as the sum of squared daily returns, ie. $V_t = \sum_{i=0}^{n} r_{t-i}^2$. They then estimated autoregressive models for each market's monthly volatility, $V_t = \alpha + \sum_{i=1}^{p} \beta_i V_{t-i} + \varepsilon_t$, choosing p to minimise Schwarz's information criterion (at the monthly frequency a single lag is sufficient) so their proxy for volatility persistence is $\hat{\beta}_1$.

The second measure of volatility persistence derives from an the estimation of GARCH model of daily stock returns, r_t, as proposed by Engle and Bollerslev (1986):

$$r_t = \beta r_{t-1} + \varepsilon_t$$
$$\varepsilon_t = \sqrt{h_t} e_t$$
$$h_t = \omega + \sum_{i-1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j-1}^{p} \gamma_i h_{t-j}$$

where e_t~ IN(0,1) and $\sum_{i-1}^{q} \alpha_i + \sum_{j-1}^{p} \gamma_i$ is the proxy for volatility persistence.

We have also considered using an I-GARCH model to estimate volatility persistence. However, Jain and Strobl (2017) have shown that most listed stocks in U.S. stock market exhibit a zero volatility persistence estimated from I-GARCH model. This is because integrated GARCH model restricts the sum of the persistent parameters to one, and only the part of the parameters $\sum_{i-1}^{q} \alpha_i$ are used to capture the volatility persistence. Similar evidence exists in Chinese stock market that most listed firms exhibit zero volatility persistence when estimated from I-GARCH model. In order to distinguish the firm-level volatility persistence, we prefer to not use the estimation of volatility persistence by I-GARCH.

The final measure of volatility we present is a range based measure proposed by Parkinson (1980). Specifically: $\sigma_t^2 = \frac{(\ln high_t - \ln low_t)^2}{4 \ln 2}$ where σ_t^2 denotes the volatility of index on day *t* while $high_t$ and low_t are the highest and lowest levels of reached by the index on day *t*; and the proxy for volatility persistence comes from an autoregressive model for range based volatility as suggested by Hsieh (1991):

$$\ln \sigma_t^2 = \alpha + \sum_{i=1}^{p} \beta_j \, ln\sigma_{t-1}^2 + v_t \qquad v_t \sim iid(0, \sigma_t^2)$$

where volatility persistence is given by $\sum_{i=1}^{p} \hat{\beta}_j$.

Whichever method is chosen, the evidence provided in Table 2.1 indicates that the Chinese stock market indices are both the most volatile, and show the greatest persistence in volatility. There are some changes among the rankings of volatility persistence in the other markets, but that persistence is well below that in the Chinese markets is clear.

The evidence provided in Table 2.1 indicates that the Chinese stock market indices are both the most volatile and show the greatest persistence in volatility. The key finding that the Chinese market exhibits the greatest volatility persistence is consistent across all three estimation methods. The rankings of the other markets by volatility persistence are sensitive to the choice of method, but that volatility persistence elsewhere is well below that in the Chinese markets is clear.

Table 2.1: Volatility and volatility persistence using key stock market indices

This table presents average monthly volatility (calculated as the sample average of each month's sum of squared daily returns) and three alternative proxies for volatility persistence constructed for the main market indices in the US, UK and Chinese stock markets over the period January 2010-December 2017. The first proxy is from an estimated autoregressive model, as used in McMillan and Evans (2015). The second is persistence in daily volatility derived from estimating a GARCH model, as implemented in Jain and Strobl (2017). The final column presents persistence in daily index level volatility persistence estimated from range based autoregressive volatility model (Hseih, 1991). Alongside each figure for volatility persistence, the table also records the position of each index in the ranking of volatility persistence estimates. This within method ranking is indicated in the integer following the comma in each case.

	Volatility	Volatility Persistence		
Sample period 2010-2017	Av. monthly volatility	McMillan and Evans	GARCH	Hseih
Shenzhen Composite Index	55.58	0.684, 1	0.992, 2	0.975, 1
Shanghai Composite Index	39.19	0.667, 2	0.998, 1	0.872, 2
FTSE100	19.54	0.486, 3	0.963, 4	0.840, 3
Dow Jones Industrial Average	15.76	0.433, 4	0.959, 6	0.838, 4
FTSE All Share Index	27.24	0.295, 7	0.990, 3	0.834, 5
NASDAQ	23.43	0.354, 6	0.955, 7	0.803, 6
S&P 500 Index	18.23	0.421, 5	0.962, 5	0.801, 7

In what follows we seek to analyse volatility persistence using company level data. We have a clear preference for using the autoregressive range based daily volatility model in this work. A key reason for this is that monthly measures of volatility ignores large amounts of information in the underlying daily data. Also, GARCH based models of volatility have been shown to overstate volatility persistence (Lamoureux and Lastrapes, 1990), and a further disadvantage of this class of models is that they do not allow for any error term in the volatility equation. Parkinson (1980) and others have argued that range based measures of volatility make far more efficient use of intra-day information. Alizadeh et al. (2002) have reported desirable properties of the conditional distribution of log range based volatility and the survey provided by Chou, Chou and Liu (2010) points to a number of successful applications of this methodology.

2.5 Potential drivers of volatility persistence

To the best of our knowledge, no study has so far evaluated a range of potential explanations for observed volatility persistence in company level data in emerging makers and in China's stock market specifically. Nor have any researchers looked into whether volatility persistence has changed in recent times. This is the gap in the literature that we seek to address.

In considering compelling potential influences on the persistence in the volatility of stock returns it is important to note that 'western' theories and concepts are not always directly applicable to China, see for example Jiang and Kim (2015).

Particular features of the Chinese stock market that influence our approach are.

i) Large numbers of Chinese listed companies are under some form of government control, and government control is likely to impact on managers' objectives and the incentives they face with respect to disclosure of information, see, for example, Piotroski, Wong, and Zhang (2015), Piotroski and Wong (2012), Gul, Kim and Qiu (2010) and Chen, Firth and Xu (2009).
ii) High levels of concentration in share ownership. Many Chinese companies often have a single dominant shareholder whose ownership far exceeds that of the second largest shareholder. These dominant shareholders are often, though not always, government related. Highly concentrated share ownership may impede the flow of information to the wider market, resulting in asymmetries in information across investors [Gul, Kim, and Qiu (2010)
iii) Daily trading on the main Chinese stock exchanges is massively dominated by the trades of large numbers of individual (retail) investors, given i) and ii) these investors operate within a relatively opaque information environment, see Chen, Firth, and Xu, (2009).

Nonetheless, we also draw on a substantial existing literature that has primarily focused on US markets, including the seminal work of Watts and Zimmerman (1978) on how accounting and financial reporting is influenced by the expected political costs associated with given outcomes; of Shleifer and Vishny (1986) on managerial entrenchment and incentive alignment affects and the impacts highly concentrated share ownership on corporate governance; and of

Grossman and Stiglitz (1980) on how the quality of the information environment impacts on the efficiency of stock markets.

In what follows we therefore investigate whether variations across companies and over time in i) the concentration of share ownership, ii) the number of state owned enterprises; iii) the number of financial analysts publishing forecasts of specific firms' performance; and iv) in institutional ownership can help predict variations in the persistence of firm level stock volatility. Before we set out our empirical strategy it is worth setting out how the existing literature informs our analysis.

2.5.1 Ownership concentration

The existing literature has long emphasised two potential effects of concentrated share ownership: entrenchment effects on the one hand, and incentive alignment effects on the other (see for example Shleifer and Vishny, 1986).

From the entrenchment effect perspective, shareholders who hold larger proportions of a given company's shares have both incentives and the opportunity to engage in self-serving behaviours. Often the dominant shareholders are closely linked to management may deter the flow of firm-specific information to the wider market if they can since they will then have the opportunity to benefit from private information, see Claessens et al. (2002) and Fan and Won (2002).

On the other hand in the case of a single dominant private investor, the investor will often have detailed knowledge of the industry the company operates in and able to actively monitor the company. A single dominant private investors may install themselves or their representatives as the CEO and the chairman of the listed company so that they can enter into the management function themselves or more effectively monitor the hired managers. This can help ensure managers' incentives are aligned with their own. Nonetheless, the dominant shareholder that can benefit from private information is unlikely to focus on improving information disclosure to a wider pool of shareholders.

Hypothesis 2.1: We expect volatility persistence to be positively associated with ownership concentration if entrenchment effects dominate or negatively associated with ownership concentration if incentive alignment effects dominate.

2.5.2 State owned enterprises

State owned enterprises (SOEs) often undertake non-commercial functions, for example they may be charged with delivering on aspects of national development strategy and/or performing social service functions, including contributing to maintaining employment levels during China's transition to a market economy, seen as important for maintaining social stability. Added to this, most SOE directors and managers are current or former government bureaucrats whose compensation and promotion prospects depend more on adherence to the SOEs' various political and social objectives than on the firm's operating and financial performance (Fan, Wong and Zhang, 2007). Compared to non-SOEs, SOEs more likely to receive financial support from government authorities and have preferential access to loans from state owned banks, so are less reliant on the stock markets to provide funding (Shen and Lin, 2016) and have close links to regulators (Chen et al., 2011). These factors suggest that investors in SOEs are likely to face an informational disadvantage.

Some prior studies have made distinction between central government controlled SOEs, hereafter CSOEs, and local government controlled SOEs, hereafter LSOEs. For example, Chen, Firth, and Xu, (2009) document that compared to LSOEs, CSOEs are subject to stricter monitoring from multiple Central Government Departments and are likely to be subjected to more stringent auditing. The focus on meeting political tasks can see top officials deviating from the wider share ownerships' targets and conflict with profits, but top officials in CSOEs who do well in their jobs by achieving government imposed objectives, tend to be rewarded with promotions that see them move up the state hierarchy. While strong monitoring by multiple departments may be good news for wider shareholders, the strong political incentives can result in limited information release or delayed release for political ends.

LSOEs tend to be further removed from direct control, and are less likely to be subjected to audits by top tier auditing companies. Laws and regulations are more difficult to enforce the further away the parties are from the centre of power and so LSOEs tend to be subject to weaker supervision and management. Again, objectives of LSOEs tend to frequently be used as a mechanism for implementing policy, contributing to maintaining employment levels during China's transition to a market economy, providing socioeconomic stability and building infrastructure. Our expectation is that self-serving behaviours associated with entrenchment effects and incentive misalignment are likely to perpetuate opacity of information available to shareholders are likely to result in greater persistence in firm level stock volatility.

Some prior studies have made distinction has been stressed between central government controlled SOEs, hereafter CSOEs and local government controlled SOEs, hereafter LSOEs. For example, Chen, Firth, and Xu, (2009) document that compared to LSOEs, CSOEs are subject to stricter monitoring from multiple Central Government Departments and are likely to be subjected to more stringent auditing. In contrast LSOEs are further removed from control, and are less likely to be subjected to audits by top tier auditing companies. Our expectation is that self-serving behaviours associated with entrenchment effects that are likely to perpetuate opacity of information available to shareholders are likely to result in persistence in firm level stock volatility.

Hypothesis 2.2: For the reasons set out above, we expect investors in SOEs to face a relatively opaque information environment, which will tend to be associated greater company level volatility persistence, as compared with non-SOEs.

Hypothesis 2.3: Among SOEs we expect investors in LSOEs to face the least transparency/ greatest opacity in the information environment, so we expect volatility persistence to be strongest in the case of local SOEs.

2.5.3 Analyst coverage

The Chinese government and its stock market regulator has actively encouraged growth in the number and quality of financial analysts. Financial analysts are in principle able to play an important intermediary role between individual listed firms and potentially large numbers of investors. Financial analysts have expertise in collecting, processing and disseminating both market and firm specific information, see related discussions in Chan and Hameed, 2006; Feng, Hu and Johansson, 2016; and Li, Lu and Ling, 2019. Forecasts provided by financial analysts have the potential to reduce information asymmetries and improve the efficiency of information flow. Once disseminated to and reflected upon by investors, it seems reasonable to hypothesize that growth in the number of analyst reports providing company specific forecasts, as well as forecasts relevant to the market as a whole, will be associated with a decline in the persistence of company level stock market volatility.

Hypothesis 2.4: The greater the number of analyst reports published in a year that provide forecasts for a given company, the greater the improvement in the information environment facing investors, so we expect a rise in the number of analyst reports on a given company to be associated with a decline in volatility persistence.

Hypothesis 2.5: The impact of analyst reports is likely to differ depending on whether the company concerned is a SOE as opposed to a non-SOE, and may differ across central and local government controlled SOEs.

2.5.4 Institutional ownership of shares

In ‘western’ stock markets, active institutional investors are more often regarded as beneficial to corporate governance, as a direct result of their use of skills, resources and sophisticated processing of information. A number of studies have looked into potential impacts of institutional share ownership. For example, Boone and White (2015) put forward arguments and evidence that institutional share ownership promotes good governance and has positive impacts on transparency and information production at the company level. That information production should be higher for companies with high institutional ownership, given the institutional owners’ professional expertise, is discussed in Bai, Philippon and Savov (2016), they argue that growth in institutional investors in the US has resulted in better informativeness and greater revelatory price efficiency.

Until relatively recently China had very few active institutional investors. But this is changing. In particular there has been considerable growth in the presence of mutual funds. Growth is also being see in the number and relevance of foreign institutional investors. Qualified Foreign Institutional Investors were introduced to the market in 2004 and were initially subject to strict quotas and capital restrictions. These quotas have increased and few are now binding, restrictions on QFIIs have lessened. Related research on Chinese financial markets includes Lin and Fu (2017) who focused on the influence of institutional ownership influence on firm performance, and found differential effects of active institutional investors (mutual funds and international investors) as opposed to other passive institutional investors on firm performance. Aggarwal et al. (2011) looked into whether growing the presence of foreign institutional investors has had a positive impact on good governance. Bae et al. (2012) have assessed whether foreign share ownership facilitates information transmission in emerging markets. Gul, Kim and Qui (2010) focus on whether the proportion of shares in foreign ownership, amongst other factors, have had a significant impact on stock price synchronicity and Chen, Du, Li and Ouyang (2013) have looked into the impact of foreign institutional ownership on Chinese stock return volatility, but did not look into any of these potential impacts on volatility persistence.

Hypothesis 2.6: A rise in the proportion of a company’s shares held by institutional investors is likely to be associated with a reduction in company level volatility persistence.

Mutual funds are among the most active institutional investors. Fund managers are pressured to provide investors with superior stock returns as their income is related to fund performance and size (Aggarwal et al., 2015). Mutual funds have expertise and incentives to monitor managers. This prompts company managers to be more concerned about performance and shareholders, discouraging them from opportunism (Ding et al., 2013). As large institutional shareholders, mutual funds they have considerable voting power and influence on share price movements than other institutional investors in China (Chan et al., 2014). They also have incentives to collect information and monitor management, minimizing information asymmetries and reducing the likelihood of fraud (Shleifer and Vishny, 1997; Lin and Fu, 2017). On this basis we expect we expect active institutional investors, particularly mutual funds, to be associated with more transparent company information and lower company level volatility persistence.

Hypothesis 2.7: We expect active institutional investors, particularly mutual funds, to be associated with more transparent company information and lower company level volatility persistence.

China's financial institutions, often state owned banks, have long held shares in some listed companies, but they tend to be relatively passive investors. To the extent that passive investors engage in trades they may be motivated by a desire, or Government instruction to take short term positions for political reasons or specific portfolio needs (see Elyasiani and Jia, 2010). This motivated Firth et al. (2016) and Lin and Fu (2017) to seek distinct impacts of active and passive institutional investors and motivates our hypothesis 2.8.

Hypothesis 2.8: Passive institutional investors are more likely to be motivated by political motivations to support delivery of SOEs broader objectives, therefore we expect passive institutional investors, particularly state owned banks and other state owned institutions, to be less informative to the wider pool of shareholders and result in greater volatility persistence.

In the next section we provide further details of how we propose to test these hypotheses using company level data.

2.6 Company level empirical analysis

2.6.1 The sample of listed companies included in our analysis

As previously stated, our database consists of daily data for all companies listed on the Shanghai or Shenzhen stock exchange. The next stage of our company level empirical work is to compile annual estimates of volatility persistence for each company using daily range data over the sample 2010-2017. The full sample includes all companies whose A-shares are listed on the Shanghai and Shenzhen Stock Exchanges that daily high and low share prices are recorded in the CSMAR database for at least 200 trading days over the years 2010 to 2017.

This approach then allows us to seek explanations for the variation in volatility persistence across companies and overtime using various company characteristics.

Table 2.2: The number of companies listed on the Shanghai and Shenzhen stock exchanges included each year of our sample

This table presents the numbers of listed companied and numbers of samples included over 2010 to 2017. The numbers of companies included in our estimation are also separated into non-SOEs (i.e. privately owned companies), SOEs (state owned companies), and the SOEs are split further into CSOEs (central state owned companies) and LSOEs (local state owned companies).

	2010	2011	2012	2013	2014	2015	2016	2017	Total
All listed companies	2107	2341	2470	2515	2631	2823	3118	3494	21499
Companies included	1631	1956	2217	2230	2033	1718	2265	2636	16686
of which: non SOEs	711	1009	1264	1299	1166	938	1401	1709	9497
all SOEs	920	947	953	931	867	780	864	927	7189
Central Gov. SOEs	271	285	283	274	272	249	280	294	2208
Local Gov. SOEs	649	662	670	657	595	531	584	633	4981
Non-SOEs	44%	52%	57%	58%	57%	55%	62%	65%	57%
SOEs	56%	48%	43%	42%	43%	45%	38%	35%	43%
CSOEs	17%	15%	13%	12%	13%	14%	12%	11%	13%
LSOEs	40%	34%	30%	29%	29%	31%	26%	24%	30%
Companies excluded	476	385	253	285	598	1104	853	848	4813
Change in exclusions		234	129	45	116	192	295	376	
% companies included	77.4	83.6	89.8	88.7	77.3	60.9	72.6	75.4	77.6
% total obs. included	9.8	11.7	13.3	13.4	12.2	10.3	13.6	15.8	100

Table 2.2 reports that at the start of our sample in 2010, there were 2,107 companies with shares listed in the Shanghai or Shenzhen stock markets, this had risen to 3,494 companies in the final year of our sample. We estimate volatility persistence for a given company in a given year if daily high and low share prices are recorded in the CSMAR database for at least 200 trading days in that year. The number of companies included in our estimation is clearly indicated in the second row of the table, and are then separated into non-SOEs (i.e. privately owned companies), SOEs, and the SOEs are split further into CSOEs and LSOEs. As well as

showing the numbers of each type of company included in the sample we indicate the percentages of the total number of included companies that are NSOEs, SOEs, CSOEs and LSOEs. It is clear that the proportion of state owned enterprises among the totals has declined over time, from 48% in 2010 to 30% in 2017.

Information on the number of listed companies that we have had to exclude from our sample in each of the years is also included in the table. In part these exclusions reflect IPOs during each year (delistings are exceptionally rare in China), but the majority of exclusions are the result of temporary, but potentially prolonged or repeated, suspensions in trading due to the regulator imposed limits on daily stock price movements, these suspensions were particularly evident in 2015.

In summary we are able to generate company level annual estimates of volatility for, on average, just under 80% of listed companies, giving us a total of 16,686 company, year observations in our core analysis.

2.6.2 Company level volatility persistence

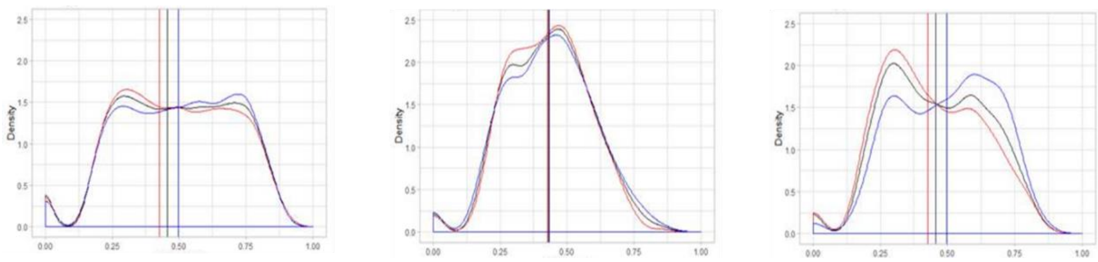
The dependent variable in our pooled (unbalanced panel) regressions is company specific level volatility persistence. Figure 2.1 illustrates the distribution of our range based estimates of volatility persistence, first across companies and over the full sample period, then for the first and last year of the sample. More specifically, for each company and each year of trading, the first step is to construct the daily range-based volatility measure using the records of the company's daily high and low price. We then use full set of observations of the constructed range based volatility measure for a given company over the trading year and estimate an autoregressive model using range-based volatility as the dependent variable. The number of lags included in autoregressive model is chosen to minimise Schwarz's Bayesian Information Criterion (BIC). We then repeat this for every company i and each year of the sample t to construct data on how volatility persistence evolves over time and how this differs by company.

The estimates are further disaggregated into those for SOEs and for non-SOEs; vertical lines are drawn at the median for each subgroup.

These charts that make up figure 2.1 demonstrate that volatility persistence varies considerably both across companies, and over time. While the median estimate of persistence for SOEs is greater than that for non SOEs, it is clear that this distinction alone is not sufficient to explain much of the observed cross-sectional variation in volatility persistence. Our search for a wider range of potential explanations therefore seems warranted.

Figure 2.1: Distribution of estimates of volatility persistence at company level

2010-2017 2010 2017



Key: All ---- SOEs --- Non SOEs ---

2.6.3 Baseline specification and core empirical strategy

In order to examine the impacts of ownership concentration, state ownership on company level volatility persistence we specify the following baseline regression:

$$\begin{aligned} volatility\ persistence_{i,t} = \beta_0 + \beta_1\ ownership\ concentration_{i,t} + \beta_2\ SOE_i \\ + controls_{i,t} + industry_i + year_t + \varepsilon_{i.t} \end{aligned} \tag{2-1}$$

where the subscript i refers the company, t refers to the year, the dependent variable volatility persistence comes from a range based autoregressive volatility model; $SOE_{i,}$ is a dummy variable which takes the value 1 when the company's largest shareholder is government related and zero otherwise; ownership concentration is given by the proportion of shares owned by the largest shareholder at beginning of year.

Our methodology framework work is close to Gul et al. (2010) who examines a number of factors that impact on information environment, proxied by synchronicity in Chinese stock market from a firm-year panel data from 1996 to 2003. Similarly, all our firm-year observations are pooled in the equation (2-1) where also include a set of control variables that may influence volatility persistence and industry and year dummy variables.

The control variables included in the regression are $size_{i,t}$ which refers to the market capitalization of list firms at the end of year; $turnover_{i,t}$ which is the turnover rate computed as volume of company i's shares traded in period t divided by the total of shares in company i at the end of the year; $btm_{i,t}$ is the book-to-market ratio. We also include the year and industry dummies to control for a potential year and industry fixed effects. In addition, the standard errors have been corrected for clustering at the firm level by using heteroscedasticity-robust standard errors.

In order to investigate whether a rise in the number reports containing company specific forecasts released by analysts on company *i* in year *t* mitigate company level volatility persistence we extend the regression by including the term $analyst_{i,t}$.

$$\begin{aligned} volatility\ persistence_{i,t} &= \beta_0 + \beta_1\ ownership\ concentration_{i,t} + \beta_2\ SOE_i + \beta_3\ analyst_{i,t} \\ &+ \gamma_j\ controls_{i,t} + industry_i + year_t + \varepsilon_{i.t} \end{aligned} \tag{2-2}$$

We then seek to test whether the impact of analyst coverage is any different for state owned companies than for non-state owned companies. This requires the inclusion of an interactive term SOE_i x $analyst_{i,t}$. The null hypothesis of there being no significant difference in the impact of analyst coverage for state owned and non-state owned enterprises respectively is given by the t-test on $\beta_4 = 0$ in equation (2-3). The other information of the model framework is consistent with that in equation (2-1).

$$\begin{aligned} volatility\ persistence_{i,t} &= \beta_0 + \beta_1\ ownership\ concentration_{i,t} + \beta_2\ SOE_i \\ &+ \beta_3\ analyst_{i,t} + \beta_4\ SOE_i \times analyst_{i,t} \\ &+ \gamma_j\ controls_{i,t} + industry_i + year_t + \varepsilon_{i.t} \end{aligned} \tag{2-3}$$

We next progress to investigate whether there is any significant difference in predictions of company level volatility persistence in the case of state owned enterprises controlled by central government as opposed to state owned enterprises that are controlled by local governments. We achieve this by replacing occurrences of SOE_i in equation (2-3) with separate terms in $CSOE_i$ and $LSOE_i$ and obtain direct t-tests of the null hypothesis for equality in the coefficients $\beta_{21} = \beta_{22}$ and $\beta_{41} = \beta_{42}$ (which can be done directly by estimating the equivalent specification in which SOE_i appears alongside $LSOE_i$ in place of $CSOE_i$). The other information of model framework is consistent with that in equation (2-1).

$$\begin{aligned} volatility\ persistence_{i,t} &= \beta_0 + \beta_1\ ownership\ concentration_{i,t} + \beta_{21}\ CSOE_i + \beta_{22}\ LSOE_i \\ &+ \beta_3\ analyst_{i,t} + \beta_{41}\ \mathrm{CSOE}_i \times analyst_{i,t} + \beta_{42} LSOE_i \times analyst_{i,t} \\ &+ \gamma_j\ controls_{i,t} + industry_i + year_t + \varepsilon_{i.t} \end{aligned} \tag{2-4}$$

The last set of core regressions involve adding institutional ownership to the equation:

$$\begin{aligned} volatility\ persistence_{i,t} = \beta_0 + \beta_1\ ownership\ concentration_{i,t} + \beta_{21}\ CSOE_i + \beta_{22}\ LSOE_i \\ +\beta_3\ analyst_{i,t} + \beta_{41}\ \mathrm{CSOE}_i \times analyst_{i,t} + \beta_{42} LSOE_i \times analyst_{i,t} \\ +\beta_5\ institutional\ ownership_{i,t} \\ +\gamma_j\ controls_{i,t} +\ industry_i +\ year_t +\ \varepsilon_{i.t} \end{aligned} \quad (2\text{-}5)$$

Subsequently we disaggregate institutional ownership into active and passive institutional investors and finally into mutual funds, QFII, financial institutions and 'other' institutions. The other information of model framework is consistent with that in equation (2-1).

2.6.4 Explanatory variables – descriptive statistics

Table 2.3: Descriptive Statistics (full sample)

The table records descriptive statistics of key explanatory variables used in our analysis for the Shanghai and Shenzhen stock markets over the sample 2010 to 2017. Ownership concentration is the proportion of each company's shares held by the largest shareholders in the beginning of the year; analyst is number of analysts who issued forecasts for company i in a year. Institutional investor is the proportion of shares owned by institutional investors at the beginning of the year. The full definition of all variables is provided in Appendix A. The sample consists of a total of 16,686 observations.

Full Sample: 2010-2017	Mean	Min	25th	Median	75th	Max	Std.
Ownership concentration	0.360	0.003	0.237	0.34	0.469	0.900	0.155
State Owned Enterprise (SOE)	0.431	0	0	0	1	1	0.495
of which Central SOE	0.132	0	0	0	0	1	0.339
Local SOE	0.299	0	0	0	1	1	0.458
Institutional Ownership	0.377	0	0.163	0.383	0.567	1	0.243
of which Active Institutions	0.068	0	0.004	0.025	0.087	1	0.103
Passive Institutions	0.309	0	0.073	0.298	0.499	1	0.24
Mutual Funds	0.067	0	0.003	0.023	0.084	1	0.102
QFII	0.002	0	0	0	0	0.177	0.009
Financial Institutions	0.088	0	0.009	0.042	0.12	1	0.117
'Other' Institutions	0.287	0	0.035	0.275	0.481	0.984	0.241
Analyst coverage	8.191	0	1	4	12	79	9.730
Firm size	22.06	18.93	21.29	21.99	22.69	28.27	1.160
Turnover ratio	7.859	0	2.901	5.347	9.968	121.88	7.938
Book-to-market ratio	0.379	0	0.211	0.332	0.494	2.068	0.233

In order to illustrate how the distribution of the variables has changed over time we also present descriptive statistics for the key explanatory variables over two cross-sections of the data, for first and final years of our sample.

In Table 2.3, the average ownership concentration, proxied by the percentage of shares held by the largest shareholder, in full sample is 36%, which indicates that shares are highly concentrated by the large shareholders. Furthermore, the mean of ownership concentration in 2010 is 36.7% as shown in Table 2.3A, which is bigger than 34.1% in 2017, suggesting the decreasing tendency of the concentrated ownership. In 2010, 56.4% of the listed firms are state owned whereas the proportion reduced dramatically to 35.2% in 2017, indicating the increasing proportion of new listed private firms during our sample periods.

On average, the percentage of shares owned by institutional investors increased from 33.2% in 2010 to 37.2% in 2017, as presented in Table 2.3A, which is consistent with Lin and Fu (2017) that institutional investors have played an increasingly important role in recent years.

Table 2.3A: Descriptive Statistics (2010 and 2017 cross sections)

Year 2010, 1631 obs.	Mean	Min	25th	Median	75th	Max	Std.
Ownership concentration	0.367	0.045	0.239	0.35	0.486	0.862	0.157
State Owned Enterprise (SOE)	0.564	0	0	1	1	1	0.496
of which Central SOE	0.166	0	0	0	0	1	0.372
Local SOE	0.398	0	0	0	1	1	0.490
Institutional Ownership	0.332	0	0.108	0.306	0.523	1	0.245
of which Active Institutions	0.09	0	0.001	0.032	0.131	1	0.128
Passive Institutions	0.242	0	0.037	0.195	0.413	0.966	0.220
Mutual Funds	0.088	0	0.001	0.030	0.127	1	0.127
QFII	0.002	0	0	0	0	0.161	0.009
Financial Institutions	0.101	0	0.004	0.044	0.151	1	0.135
‘Other’ Institutions	0.229	0	0.017	0.170	0.400	0.966	0.220
Analyst coverage	9.746	0	1	5	15	79	11.58
Year 2017, 2636 obs.	Mean	Min	25th	Median	75th	Max	Std.
Ownership concentration	0.341	0.042	0.225	0.321	0.439	0.891	0.148
State Owned Enterprise (SOE)	0.352	0	0	0	1	1	0.478
of which Central SOE	0.112	0	0	0	0	1	0.315
Local SOE	0.24	0	0	0	0	1	0.427
Institutional Ownership	0.372	0	0.153	0.383	0.568	1	0.245
of which Active Institutions	0.051	0	0.008	0.027	0.067	0.569	0.065
Passive Institutions	0.321	0	0.072	0.325	0.514	0.985	0.245
Mutual Funds	0.049	0	0.007	0.026	0.065	0.569	0.064
QFII	0.002	0	0	0	0	0.159	0.008
Financial Institutions	0.075	0	0.015	0.048	0.104	0.987	0.085
‘Other’ Institutions	0.296	0	0.038	0.294	0.490	0.984	0.243
Analyst coverage	8.597	0	1	4	13	66	10.43

Table 2.4 presents the matrix of Pearson pairwise correlations between our key variables. Volatility persistence is positively and significantly correlated with ownership concentration

and SOE, which is in line with Hypotheses 2.1 and 2.2, while these measures are negatively correlated with ownership by investment fund and analyst coverage, which is consistent with Hypotheses 2.5 and 2.7. The correlation between ownership concentration and institutional ownership are positively correlated and significant at 1% level, which indicates the largest shareholder of the listed firm is likely from institutional investors.

Table 2.4: Correlation Matrix

The table records correlation matrix of key variables used in our analysis for the Shanghai and Shenzhen stock markets over the sample 2010 to 2017. PER refers to the volatility persistence estimated from range based autoregressive volatility model; OWN is the percentage of shares owned by the largest shareholder at beginning of year; SOE is an indicator variable on the nature of largest shareholder and equals to one if the largest shareholder of listed firm is government related, and zero if non-government related; INSTITUTION is the percentage of shares owned by institutional investors at beginning of year; FUND, QFII, FINANCE and OTHER refer to the disaggregated institutional ownership by investment fund, foreign investor, financial institution and other investors, as discussed earlier; ANA is the analysis coverage as the number of analysts who issued forecasts for a firm in a year; SIZE is the market capitalization of list firms; TURN and BTM refer to turnover ratio and book-to-market ratio respectively. Superscripts ***, **, and * stand for statistical significance at the 1%, 5%, and 10% levels respectively.

	PER	OWN	SOE	INSTITUTION	FUND	QFII
PER	1	0.02**	0.033***	0.053***	-0.157***	0.005
OWN		1	0.195***	0.272***	-0.032***	-0.019**
SOE			1	0.351***	-0.09***	0.004
INSTITUTION				1	0.243***	0.081***
FUND					1	0.085***
QFII						1

	FINANCE	OTHER	ANA	SIZE	TURN	BTM
PER	-0.141***	0.121***	-0.068***	0.183***	0.27***	-0.108***
OWN	-0.025***	0.288***	0.065***	0.083***	-0.061***	0.106***
SOE	-0.087***	0.397***	-0.025***	0.298***	-0.199***	0.223***
INSTITUTION	0.261***	0.881***	0.27***	0.572***	-0.427***	0.156***
FUND	0.936***	-0.212***	0.516***	0.115***	-0.068***	-0.113***
QFII	0.086***	0.002	0.193***	0.138***	-0.048***	0.067***
FINANCE	1	-0.226***	0.524***	0.146***	-0.081***	-0.087***
OTHER		1	0.011	0.501***	-0.39***	0.197***
ANA			1	0.431***	-0.132***	0.017**
SIZE				1	-0.387***	0.206***
TURN					1	-0.333***
BTM						1

2.6.5 Core results

The baseline regression estimates of equation (2-1) are set out Table 2.5, column 1. This regression seeks to determine whether concentration of share ownership (measured by the proportion of shares owned by the largest shareholder at the start of the year) alongside a dummy variable = 1 if the company is an SOE and =0 otherwise, can contribute to predicting significant variation in volatility persistence across companies and over time. The results are in line with our expectations and consistent with hypotheses 2.1 and 2.2 as set out in section 2.4: greater concentration of share ownership predicts greater company level volatility persistence, and company level volatility persistence is predicted to be higher in the when the company in question is an SOE.

The second regression, column 2, introduces analyst coverage, i.e. the number of analysts producing forecasts of company i's performance in year t as an additional explanatory variable, in line with equation (2-2). This variable attracts a significant negative coefficient implying that greater analyst coverage is associated with a decline in volatility persistence. This is consistent with analyst coverage improving the information environment facing investors, thereby offering support to hypothesis 2.4.

In column 3 we estimate equation (2-3) which seeks to assess whether there is any difference in the impact of greater analyst coverage on volatility persistence when the company the analysts are reporting on is a state owned enterprise. The significant negative coefficient on SOE_i x $analyst_{it}$ indicates that the marginal decline in volatility persistence is greater in the case of an additional analyst report on a state owned enterprise, than that following release of another analyst report on a non-state owned enterprise, holding all else equal. Column 4 the builds on the previous specification by splitting state ownership into central government ownership and local government ownership as set out in equation (2-4). Column 5 shows results for a simple reparameterisation of this equation which simply includes SOE_i in place of $CSOE_i$ alongside $LSOE_i$ and is a convenient way to allow us to test whether there are significant differences in the coefficients. The estimated coefficients on $CSOE_i$ and $LSOE_i$ are both 0.016 and are significantly different from 0, so *certeris paribus* companies that are state owned enterprises experience greater persistence in stock market volatility than non-state owned enterprises.

Table 2.5: Investigating the impacts of ownership concentration, state ownership and analyst coverage on company level volatility persistence.

This table reports regression results used to investigate the impacts of ownership concentration, state ownership and analyst coverage on volatility persistence. The full sample includes all companies whose A-shares are listed on the Shanghai and Shenzhen Stock Exchanges that daily high and low share prices are recorded in the CSMAR database for at least 200 trading days over the years 2010 to 2017. The dependent variable is volatility persistence estimated for each company and every year from range based autoregressive volatility model. The key independent variables are ownership concentration, state ownership and analyst coverage. The full definitions of all variables are provided in Appendix A. The sample size is 16,686. Year and industry dummies are included, standard errors are clustered at firm level. ***, ** and * denote significance at the 1%, 5% and 10% significance levels respectively and t-ratios are given in parentheses.

Dependent variable: Volatility Persistence	[1]	[2]	[3]	[4]	[5]
Ownership concentration	0.015*	0.020**	0.020**	0.021**	0.021**
	(1.83)	(2.45)	(2.50)	(2.54)	(2.54)
State owned enterprice (SOE)	0.016***	0.011***	0.016***		0.016***
	(5.82)	(3.98)	(4.95)		(3.19)
Central SOE (C_SOE)				0.016***	
				(4.59)	
Local SOE (L_SOE)				0.016***	0.001
				(3.19)	(0.14)
Analyst coverage		-0.131***	-0.101***	-0.102***	-0.102***
		(-8.20)	(-5.16)	(-5.17)	(-5.17)
SOE.Analyst coverage			-0.071**		-0.080**
			(-2.55)		(-2.00)
C_SOE.Analyst coverage				-0.080**	
				(-2.00)	
L_SOE.Analyst coverage				-0.067**	0.013
				(-2.13)	(0.31)
Size	0.019***	0.026***	0.026***	0.027***	0.027***
Turnover	0.005***	0.005***	0.005***	0.005***	0.005***
Book-to-market ratio	0.031***	0.026***	0.027***	0.027***	0.027***
Adjusted R^2	0.445	0.448	0.448	0.448	0.448

Turning to the point estimates of the effects of analyst reports for the different types of companies, and focusing on the coefficient on $analyst_{i,t}$ and on each of the interactive terms $CSOE_i$ x $analyst_{i,t}$ and $LSOE_i$ x $analyst_{i,t}$ the results indicate that an increase in analyst coverage mitigates volatility persistence and that the marginal effect is strongest for central government controlled SOEs (at -0.182=-0.102-0.080), a little weaker for local government controlled SOEs (at -0.169=-0.102-0.067) and weakest for non-SOEs (at -0.102). However, looking at column [5] we can deduce that the effect of another analyst report on volatility persistence of state owned companies is estimated to be significantly stronger for state owned enterprises (-0.182) relative to non-state owned enterprises (-0.102), but is not significantly different across central or locally controlled state owned enterprises. The relevant t-statistics, given in the last two rows of column [5] are t=-2.0 and t=0.31 respectively.

Table 2.6: Investigating the impacts of institutional ownership and analyst coverage on company level volatility persistence.

This table reports regression results used to investigate the impacts of institutional ownership on volatility persistence. The full sample includes all companies whose A-shares are listed on the Shanghai and Shenzhen Stock Exchanges that daily high and low share prices are recorded in the CSMAR database for at least 200 trading days over the years 2010 to 2017. The dependent variable is volatility persistence for company i in year t as estimated from set of range based autoregressive volatility models. The key additional explanatory variables are the proportion of shares held by institutions, which are disaggregated into active and passive institutions or into mutual funds, qualified foreign institutional investors, financial institutions and 'other' institutions. The full definitions of all variables are provided in Appendix A. The sample size is 16,686. Other controls variables, size, turnover and book to market rations, as well as year and industry dummies are included as before, but are omitted from the table to save space. Standard errors are clustered at firm level. ***, ** and * denote significance at the 1%, 5% and 10% significance levels respectively and t-ratios are given in parentheses.

Dependent variable: Volatility Persistence	[1]	[2]	[3]
Institutional Ownership	0.009		
	(1.40)		
of which: active institutions		-0.159***	
		(-11.0)	
passive institutions		0.030***	
		(-4.47)	
mutual funds			-0.169***
			(-4.93)
QFII			0.099
			(0.73)
financial institutions			0.031***
			(4.54)
other			0.050***
			(6.23)
Central SOE (C_SOE)	0.016***	0.014***	0.014***
	(3.08)	(2.82)	(2.78)
Local SOE (L_SOE)	0.016***	0.014***	0.014***
	(4.32)	(3.65)	(3.65)
Analyst coverage	-0.102***	-0.01	-0.009
	(-5.57)	(-0.50)	(-0.44)
C_SOE.Analyst coverage	-0.073***	-0.098***	-0.093***
	(-1.95)	(-2.61)	(-2.49)
L_SOE.Analyst coverage	-0.065***	-0.079***	-0.079***
	(-2.30)	(-2.80)	(-2.83)
Adjusted R^2	0.448	0.453	0.453

Table 2.6 adds institutional ownership to the factors explaining volatility persistence in line with equation (2-5). Initially in column [1], all institutional owners are treated the same. In column [2] institutional ownership is disaggregated into active and passive investors and in column [3], separate effects are estimated for investment funds, qualified foreign institutional investors (QFII), financial institutions and ‘other’ institutions.

The first result in Table 2.6 indicates that the percentage of shares company i’s shares held by institutional investors does not have a significant impact on the persistence of volatility. However, once we use Lin and Fu’s (2017) disaggregation into share holdings active institutional investors and passive institutional investors we find that a higher percentage of a company’s shares held by active institutional investors is associated with lower the persistence in that company’s stock volatility. In contrast, the greater the percentage of shares held by passive institutional investors, the greater persistence of stock price volatility at company level. Disaggregating further, column 3 shows that an increase in the percentage of shares held by mutual funds is estimated to have the strongest impact in mitigating volatility persistence.

It’s also relevant to point out that the separate analyst coverage term loses significance as soon as institutional ownership is disaggregated. It seems that active investors, and more specifically mutual funds eliminate the significance of the separate effect of analyst coverage, which is now only significant in the case of state owned enterprises. This could be consistent with limited demand for analyst reports from retail investors; it may be that mutual funds are both the main producers and the main users of analyst reports.

2.7 Robustness checks

In order to check the robustness our core findings we conduct a several additional checks.

2.7.1 Estimating separate regressions for non-SOEs and SOEs

The first check is to re-run the regressions in table 2.6 columns for two sub-samples of the dataset, the first sub-sample includes all observations for non-state owned enterprises, and the second subsample includes all observations for state owned enterprises.

Our key findings remain: active institutions, particularly mutual funds are associated with lower company level volatility persistence; greater share ownership by passive institutions, particularly those in the ‘other’ institutions category is associated with greater volatility persistence. Greater analyst coverage is associated with less volatility persistence, but the this significance of this effect is only apparent prior to disaggregating institutional ownership, so it seems that the impact is better captured in the active institutional ownership and mutual funds variables – a result that could be consistent with weak demand from retail investors for analyst reports. Active institutional ownership and mutual funds again have a stronger estimated impact in mitigating volatility persistence in SOEs than in non-SOEs, but there's no significant difference in the estimated impacts for local government controlled SOEs and central government controlled SOEs.

Table 2.7: Investigating the impacts of institutional ownership and analyst coverage on company level volatility persistence, separate regressions for non-SOEs and SOEs.

This table reports regression results used to investigate the impacts of institutional ownership and analyst coverage on volatility persistence. Where separate regressions are run for the observations involving non-SOEs and SOEs respectively. The full sample includes all companies whose A-shares are listed on the Shanghai and Shenzhen Stock Exchanges that daily high and low share prices are recorded in the CSMAR database for at least 200 trading days over the years 2010 to 2017. The dependent variable is volatility persistence for company i in year t as estimated from set of range based autoregressive volatility models, this and all other variables are as set out in Table 2.6. Other controls variables, size, turnover and book to market rations, as well as year and industry dummies are included as before, but are omitted from the table to save space. Standard errors are clustered at firm level. ***, ** and * denote significance at the 1%, 5% and 10% significance levels respectively and t-ratios are given in parentheses.

Dependent variable:	Non-SOEs (no. obs = 9497)			SOEs (no. obs = 7189)		
Volatility Persistence	[1]	[2]	[3]	[4]	[5]	[6]
Institutional Ownership	-0.001			0.021**		
	(-0.06)			(1.99)		
of which: active institutions		-0.171***			-0.137***	
		(-9.47)			(-4.96)	
passive institutions		0.030***			0.032***	
		(3.23)			(2.94)	
mutual funds			-0.138***			-0.170***
			(-2.77)			(-3.27)
QFII			0.226			-0.277
			(1.16)			(-1.14)
financial institutions			-0.034			0.034
			(-0.76)			(0.80)
other institutions			0.031***			0.031***
			(3.35)			(2.90)
Local SOE (LSOE)				0.003	0.002	0.002
				(0.62)	(0.33)	(0.32)
Analyst coverage	-0.107***	0.007	0.007	-0.151***	-0.070*	-0.071*
	(-5.16)	(0.28)	(0.30)	(-3.94)	(-1.71)	(-1.72)
LSOE x Analyst coverage				0.010	0.020	0.023
				(0.24)	(0.48)	(0.53)
Adjusted R^2	0.453	0.453	0.452	0.465	0.469	0.468

2.7.2 Controlling for market wide volatility

In our second check on the robustness our core findings we seek to control for market-wide volatility to better isolate a company specific measure of volatility and then re-estimate company level volatility persistence. More specifically, we first regress each company's daily range based volatility on the equivalently constructed market wide measure of range basd volatility and save the residual. This residual is the component of company level volatility that cannot be predicted using the market wide measure of stock market volatility. We then estimate new autoregressive models in the (log of) company specific volatility and obtain a corresponding proxy for persistence in this company specific component of volatility. We then repeat the key regressions set out in Table 2.6 using this new proxy for persistence in company specific volatility. The results are reported in Table 2.8. Once again, the key findings seen in our earlier results remain. There is just one new finding, the large significant positive coefficient on QFII, which suggests that an increase in foreign institutional share holdings is associated with higher volatility persistence.

2.7.3 Checking the sensitivity of the core results to exclusion of data from 2015 and 2016

The Chinese stock market went through particularly turbulent period in 2015 and in the early part of 2016. In Table 2.9 we report results obtained by running the regressions reported in Table 2.6 having excluded all company and year observations from 2015 and 2016. The estimation results are presented in Table 2.9, and the main point to note is that our core results again remain robust.

Table 2.8: Controlling for market-wide volatility, to better isolate the company specific component of volatility and volatility persistence.

This table reports regression results used to investigate the impacts of institutional ownership and analyst coverage on volatility persistence in which the proxy for volatility persistence has been constructed from a measure of the component of company level volatility that cannot be explained by market wide volatility. The sample includes all companies whose A-shares are listed on the Shanghai and Shenzhen Stock Exchanges for which daily high and low share prices are recorded in the CSMAR database for at least 200 trading days over the years 2010 to 2017. Other controls variables, size, turnover and book to market rations, as well as year and industry dummies are included as before, but are omitted from the table to save space. Standard errors are clustered at firm level. ***, ** and * denote significance at the 1%, 5% and 10% significance levels respectively and t-ratios are given in parentheses.

Dependent variable: Volatility Persistence	[1]	[2]	[3]
Institutional Ownership	0.011		
	(1.46)		
of which: active institutions		-0.287***	
		(-16.7)	
passive institutions		0.049***	
		(6.09)	
mutual funds			-0.299***
			(-7.40)
QFII			0.375***
			(2.32)
financial institutions			0.007
			(0.19)
other institutions			0.050***
			(6.23)
Central SOE (CSOE)	0.017***	0.015***	0.014***
	(2.84)	(2.45)	(2.38)
Local SOE (LSOE)	0.026***	0.022***	0.022***
	(5.88)	(4.91)	(4.90)
Analyst coverage	-0.180***	0.02	0.016
	(-8.23)	(0.82)	(0.65)
CSOE x Analyst coverage	-0.075*	-0.118***	-0.108***
	(-1.67)	(-2.68)	(-2.43)
LSOE x Analyst coverage	-0.068**	-0.093***	-0.095***
	(-2.04)	(-2.80)	(-2.87)
Adjusted R^2	0.137	0.157	0.157

Table 2.9: Investigating the drivers of company level volatility persistence having dropped the two years in which China's stock market experienced extreme turbulence

This table reports regression results used to investigate the impacts of institutional ownership on volatility persistence. The sample includes all companies whose A-shares are listed on the Shanghai and Shenzhen Stock Exchanges that daily high and low share prices are recorded in the CSMAR database for at least 200 trading days over the years 2010 to 2014 and 2017. The dependent variable is volatility persistence for company *i* in year *t* as estimated from set of range based autoregressive volatility models, this and all other variables are as set out in Table 2.5. Other controls variables, size, turnover and book to market rations, as well as year and industry dummies are included as before, but are omitted from the table to save space. Standard errors are clustered at firm level. ***, ** and * denote significance at the 1%, 5% and 10% significance levels respectively and t-ratios are given in parentheses.

Dependent variable: Volatility Persistence	[1]	[2]	[3]
Institutional Ownership	0.025***		
	(3.02)		
of which: active institutions		-0.158***	
		(-9.53)	
passive institutions		0.051***	
		(6.05)	
mutual funds			-0.191***
			(-4.20)
QFII			0.195
			(1.00)
financial institutions			0.031
			(0.761)
other			0.051***
			(6.10)
Central SOE (CSOE)	0.014**	0.012**	0.012**
	(2.35)	(2.08)	(2.04)
Local SOE (LSOE)	0.019***	0.016***	0.016***
	(4.51)	(3.82)	(3.82)
Analyst coverage	-0.147***	-0.018	-0.02
	(-6.46)	(-0.70)	(-0.78)
CSOE x Analyst coverage	-0.069	-0.097**	-0.092**
	(-1.55)	(-2.16)	(-2.04)
LSOE x Analyst coverage	-0.055	-0.071**	-0.071**
	(-1.57)	(-2.01)	(-2.02)
Adjusted R^2	0.212	0.221	0.222

2.8 Conclusions

In this chapter we have demonstrated that the volatility of China's stock returns tends to be greater, and to persist for longer, than is typical in 'western' markets. To the best of our knowledge, there has been no in depth exploration of potential explanations on the drivers of volatility persistence. This is the gap in the literature that we have sought to address. It is hoped that the findings contained in the Chapter will be of interest to financial practitioners in understanding the dynamic patterns of volatility in the Chinese stock market, and to financial regulators interested in the policy implications of improving the information environment in Chinese stock market.

We initially documented this evidence of high volatility using range based measures of stock market volatility at the level of market indices and then moved on to examine volatility persistence in company stock price data.

It is easy to argue that identifying and monitoring factors that have influenced high persistence in Chinese stock market volatility have gained in significance and relevance over time. The size of the market has grown at a fast pace, not least over the last decade. The number and types of listed companies have expanded such that the market is now less dominated by shares in state owned enterprises, and the kinds of investors who participate in the market are also expanding. The Chinese government continues to actively encourage many of these developments, for example, by encouraging the development domestic fund management institutions, progressively increasing the openness of the markets to trades by international investors and some through incentivising some of the regulatory and disclosure changes required for selected Chinese shares to be included in the MSCI emerging markets index.

We proposed that high volatility persistence may be an outcome of the information environment that the majority of Chinese stock market investors operate in. We further proposed that opacity of the information environment that the majority of Chinese stock market investors operate in.

We went on to suggest that opacity in the information environment is likely to greatest when a single shareholder holds a high proportion of the total shares in a given firm; and when the largest shareholders are government related. Against this, we noted that reforms of state ownership/control and the relatively recent growth in institutional trading may have improved the information environment.

We investigated the validity of these arguments using an extensive company level dataset and found that i) volatility persistence is greatest when the largest shareholder is 'local government-related', and is lowest when the largest shareholder is 'non-government related'; ii) irrespective of government ownership, volatility persistence is higher when share ownership is highly concentrated; and iii) growth in institutional investment, in particular shareholdings by mutual funds do seem be associated with a decline in company level volatility persistence.

Interestingly, growth in the number of analyst reports made available that refer to the prospects of a given company seems to have had limited effectiveness in mitigating volatility persistence independently of the growth in active institutional investors. We suggest that a possible limiting factor is the fact that retail investors' demand for such information may remain limited.

We infer that continued growth in active institutional investors, particularly mutual funds, along with continuing reforms of state ownership/control look to be promising ways to mitigate the persistence of volatility in the Chinese stock market. We also caution that at present the provision of more company specific information to retail investors may result in only very minimal changes in volatility dynamics. To the best of our knowledge, these findings focusing on factors that influence the persistence of volatility in Chinese stock returns are entirely new**.**

Overall, our these findings provide the insights of policy implications for financial regulators in Chinese stock market that continued growth in financial analyst and active institutional investors plays the important roles in reducing the information asymmetry in the markets. However, no evidence of such effect is found for passive institutional investors.

Chapter 3

3. Institutional trading in volatile markets: Evidence from Chinese stock markets

3.1 Introduction

Equity markets in China have expanded fast since the re-establishment of securities markets in Shanghai and Shenzhen in early 1990s. The two Chinese stock exchanges combined now constitute the second largest capital market in the world by total stock capitalization after the U.S., having surpassed Japan in 2014. Chinese stocks have become increasingly popular with global investors who are seeking to benefit from international risk sharing and portfolio diversification. However, the extreme price swings and apparent irrational behaviour experienced in Chinese stock markets have raised concerns amongst policy makers, regulators and global investors, particularly given the strong and growing dependence of the global economy on the Chinese economy (Tian *et. al.* 2018). This chapter seeks to examine whether the trading activity by institutional investors or retail investors exacerbate the extreme market movements in China's stock market where price limit rule is imposed, and the impact of these trading activity on the post extreme days for price-limit-hitting stocks. Understanding the sources and patterns of market swings in China's stock market brings valuable insights to the risk management for financial practitioners as well as to the evaluations of the price limit role for policymakers in extreme market movement days.

In order to identify the sources of extreme swings in stock prices, two prior studies are key: Dennis and Strickland (2002) and Tian *et al.* (2018). Both these studies use institutional ownership data as a proxy that is intended to capture the influence of institutional traders. One disadvantage of these ownership data is that they are only available on a quarterly basis, while the extreme market movements are captured on a daily basis. In our view, quarterly data on institutional holdings of each firm's stock is too restrictive and imprecise to appropriately proxy the influence of institutional traders on extreme market movement days (several of which sometimes occur within a given quarter in Chinese markets); we suggest that use of his proxy is likely to conceal important details about the shorter-term activities of the traders in question. As suggested, albeit in different contexts, by Campbell, *et al.* (2009) and Boehmer and Kelley (2009) among others, we argue that it is vital to seek an alternative, higher

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An earlier version of this chapter has benefited from the comments on presentation at 6th young finance conference at University of Sussex in June 13-14, 2019.

frequency, proxy for institutional trading in order to have a better chance of explaining whether institutional trading plays a role in generating and/or prolonging extreme market swings or alternatively to provide convincing evidence of market stabilizing effects.

In our study we exploit available daily cash flow data relating to individual firms' stocks to construct a more appropriate proxy for the daily trading activities of institutions. Such data has previously been found to play an important role in explaining stock returns[2]. For example, Yang and Yang (2019) find that an index of inflow-outflow imbalances constructed from available cash flow data plays an important role in explaining excess stock returns in Chinese markets. Our proposed proxy relies on daily cash flow data on transactions by value, obtained from the RESSET database. From these data we focus purely on those transactions on a given trading day that have a value in excess of one million Chinese RMB, i.e. the largest category of transactions that has consistently been recorded in the database throughout our sample period. Given available data on the very low percentage of retail accounts for which the total market value of holdings exceeds one million RMB[3], it seems reasonable to assume that virtually all of these high value transactions will have been made by institutional investors. Specifically, our proxy is constructed as the net value of the total of the largest value category of inflows (purchases) and total of the largest value category of outflows (sales). Importantly, the utilization of daily cash flow data in our proxy allows us to investigate the impact of daily institutional trading behaviour on firm-level stock returns both on, and subsequent to, extreme market movement days.

In our empirical analysis we find that i) institutional investors tend to be net buyers (sellers) of stocks on extreme market up (down) days; ii) there is consistent and significant evidence, across both Chinese markets, of institutional trading having a destabilizing influence on abnormal stock returns. Our institutional trading proxy is also correlated with a reduction in abnormal turnover on extreme down days. These findings contrast with those of Tian *et al.* (*op cit.*), consistent with our belief that the quarterly proxy used in this prior research does not incorporate the necessary level of detail required to capture the impacts of daily institutional trading behaviour. Therefore, we add value to this strand of literature by proposing a more appropriate proxy for institutional investors' daily trading.

[2] See among others, Jotikasthira *et al.*, 2012; Kirchler *et al.*, 2015; Razena *et al.*, 2017; Jiang and Yuksel, 2017; Yang and Yang, 2019.

[3] According to retail investors' holding value data from China Securities Depository & Clearing Corporation Limited, the percentage of retail accounts whose stock holding market value exceeding 1 million in 2011 and 2016 are only 0.82% and 2.75%.

An important factor omitted entirely from this previous study of extreme market swings in the Chinese stock market relates to the existence and role of regulator imposed limits on permitted stock price movements within a given trading day[4]. (This is not an issue for the Dennis and Strickland (*op cit.*) study, since there are no limits to daily stock price movements in use in the U.S. exchanges.) Unsurprisingly, on extreme market movement days a substantial number of Chinese stocks hit the upper (lower) price limit. Given the frequent binding nature of these regulator imposed price limits, we argue that it is essential for a complete analysis of the impacts of institutional trading to allow for the potentially conflating impacts of binding price limits, and to incorporate information on what happens to abnormal returns in the days after price limits are hit. With this in mind, in contrast to the previous studies of extreme movement days, our investigation includes extensive analysis of abnormal stock returns on the days following extreme market movement days. In this chapter, another value we add to the study of China's extreme market days is to consider the effect of the price limit on the stock returns of both extreme days and post extreme days.

So, in our analysis of individual firms' abnormal stock returns on the days following extreme market movement days, we are particularly interested in what subsequently happens to the abnormal returns of those stocks that hit a regulator imposed price limit during trading on a given extreme market movement days. The existing literature provides mixed evidence on whether price limits lead to 'delayed price discovery' or to 'price reversal'. Evidence on this for Chinese stock markets includes Chen, *et al.*, 2005; Wong *et al.* 2009 and Li, *et al.*, 2014, Chen, *et al.*, 2019. The regulators' stated objective with respect to the imposition of price limits is that they are intended to calm the markets, giving would-be active investors time to reflect on fundamentals. Subsequent price reversal would consistent with correction of a market whose participants come to the belief that traders had over-reacted. However, in rational markets, price limits delay adjustment that reflects changes in fundamentals.

Our own post-extreme day analysis is closest to that of Chen *et al.* (2019), who examine the impact of trading behaviour of large investors in regular stocks that hit the 10% upper price limit in the Chinese stock markets; following their lead we investigate subsequent abnormal firm-level returns over a range of different horizons, from overnight and rising to a horizon of a maximum of 120 days. We find that firm-level abnormal returns on the days subsequent to extreme market movement days continue to be consistently positive (negative) for at least two subsequent days in the case of stocks that hit the +/-10% price limit during trading on the

[4] The Chinese stock market regulator imposes a (+/-)10% daily limit on price movements for regular stocks and a daily limit of +/-5% for special treatment stocks.

initial extreme market movement day. This evidence is consistent with the binding price limit acting to strengthen a delay in price discovery. We further find evidence of a longer-run price reversal effect for those stocks that hit the lower price limit on extreme market downward movement days, but that no such longer-run effects for stocks that hit the upper price limit on extreme market upward movement days.

Lastly we investigate whether the net purchases (sales) conducted by institutional investors on extreme market movement days are significant predictors of subsequent firm-level abnormal returns. Our results are consistent with a delayed price discovery effect that continues to destabilize markets. Interestingly, we find that the high value net trades conducted by institutional investors are significant predictors of returns in days subsequent to extreme market movement days in both markets. We further show that this predictive power is strongest for regular, as opposed to special treatment, stocks.

In summary, this Chapter contributes to the existing literature in four ways: first, we improve on existing studies that have relied on quarterly data to proxy for the influence of institutional investors by constructing and using a new proxy that uses daily cash flow records on large transactions by value to better capture the daily trading activity of institutional investors. More importantly, different from Chen *et al.* (*op cit.*), the proxy of institutional trading in our study is sourced from open database, which facilitates the future study on the investigation of institutional trading behaviour. Second, we highlight the importance of price limits in influencing how extreme market swings impact on both the immediate and subsequent days performance of firm-level stock returns. Evidence suggests the different return patterns of post extreme market swings compared to the existing studies based on all trading-days investigation, which may be related to the high trading sentiment on and around extreme market movement days. Third, we investigate whether high value net trades in individual shares on extreme market movement days are significant predictors of firm-level abnormal returns in the days following extreme market movement days in both the Chinese stock markets. Our findings suggest that previous research, which relied on quarterly institutional ownership data and ignored the impacts of price limits, was unable to capture important destabilising impacts of that can be attributed to shorter-term institutional trading activity. In short, we identify clear circumstances in which the activities of institutional investors drive abnormal returns. Lastly, our findings provide policy implications of the destabilizing role played by price limit rules in market swings, which also are supportive of the active steps the regulators are undertaking towards the financial liberalization of price limit such as the launch of Shanghai's Star Market[5] at July 22, 2019.

The rest of the Chapter is organized as follows. Section 3.3 provides the literature review. Section 3.3 develops the relevant testable hypotheses. Section 3.4 describes data sources and definitions of variables, and is followed by an explanation of our methodological approach in section 3.5. Our key findings are summarised in section 3.6. Section 3.7 concludes. All the extreme movement days identified in the Shanghai and Shenzhen stock markets over our sample can be found in Appendix B, while detailed analysis of special treatment stocks can be found in and Appendix C.

3.2 Literature Review

The evidence in the existing literature on whether institutional investors stabilize or destabilize the stock market remains mixed and inconclusive. Using new data on the holdings of 769 tax-exempt funds, Lakonishok et al. (1992) investigate the effect of institutional trading on stock price, and find institutional investors destabilize the stock price by exhibiting herd and positive-feedback trading behaviours. Dennis and Strickland (2002) provide results of a destabilizing effect of institutional trading behaviour on U.S. extreme market movement days. On the contrary, others argue that the trading behaviours of institutional investors play a stabilizing effect on stock market. Wermers (1999) analyses the trading activity of the mutual fund and finds that the impact of herding by mutual funds has helped to speed the price-adjustment of the stock price. Li and Wong (2010) examine the short-run dynamic relation between daily institutional trading and stock price volatility in China's stock market and document the stabilizing effect of institutional trading by reducing the stock return volatility.

In order to understand the source of stock market swings, a series of recent studies focus particularly on the examination of stabilizing or destabilizing effect of institutional investors on the extreme market movement days. Dennis and Strickland (2002) is the first Chapter to investigate extreme market movement days experienced in the U.S. stock market, in which the extreme days are defined with the days having the market return exceeding roughly two or three standard deviations above or below the mean. They find that firm-level abnormal returns recorded on extreme days are positively correlated with the percentage of the relevant

[5] Shanghai's Star Market has been viewed as the testing ground of Chinese stock market reforms. There is no daily limit imposed for new listed stocks on the first five trading days, and after that a 20% daily limit was adopted, instead of the 10% daily limit for other boards of the A-share market. The increase of price limit level is thus expected to hinder institutional investors' destructive pump-and-dump trading behaviour through price limit hit (See Chen *et al.,* 2019).

firms' shares that are owned by institutions. As a result, they argue that institutional ownership is destabilizing. In contrast, more closely related research by Tian et al. (2018), while using the identical approach applied to Chinese firm-level data, document a stabilizing effect of institutional ownership on firm-level abnormal returns, so conclude that institutional trading acts to stabilize the Chinese stock markets over the period from 2003 to 2014. However, both of these two literature use the quarterly institutional ownership as the proxy of institutional trading in extreme market movement days. As suggested by Campbell, et al. (2009) and Boehmer and Kelley (2009), the quarterly proxy is likely to conceal important details about the shorter-term activities of the traders. To fill this research gap, we seek for a more appropriate proxy of daily institutional trading in this chapter to investigate the effect of institutional trading behaviour on stock market returns on extreme market movement days.

In addition, another important factor omitted entirely by Tian et al. (2018) on examination of extreme market movement days in Chinese stock market is that a large number of stocks hit upper (lower) price limit on the up (down) extreme days, leaving it as another research gap to examine the stock returns in the post extreme days for these price-limit-hit stocks. The existing literature provides mixed evidence on whether price limits lead to 'delayed price discovery' or to 'price reversal'. Chen et al. (2005) investigate the effects of price limits on Chinese listed A shares from 1996 to 2003. They provide evidence of a delayed effect on upward price movements but the same is not true of downward price movements. Similarly, Wong et al. (2009) investigate the so-called magnet effects of price limits in Shanghai Stock Exchange from Jan 2002 to Dec 2002 and again find evidence of delayed price discovery associated after stocks hit the price ceiling in a given trading day and, in contrast, find evidence of subsequent price reversal in stocks that hit price floor within a given trading day. On the other hand, Li et al. (2014) claim to present evidence that supports the conclusion that price limits are effective in preventing price changes from continuing when examining China's listed A shares as well as Chinese, Hong Kong (H shares) and New York (N shares). The period they focus upon includes new listing data up to May 2011. Therefore, we fill this research gap by testing the delayed price discovery process for price-limit-hitting stocks on extreme market movement days.

In summary, this chapter fills the research gap by seeking a more appropriate proxy for daily institutional trading to examine the stabilizing or destabilizing role played by institutional investors on extreme market movement days in the Chinese stock market. In addition, this chapter also extends the extreme days research into post extreme days so as to conduct a complete investigation of the stock return patterns for shares hitting the price limit.

3.3 Empirical hypotheses

3.3.1 The effects of institutional trading on extreme market movement days

Institutional trading behaviour has attracted considerable attention in the finance literature. Two well-documented types of trading behaviour are herding, which refers to the propensity of investors to follow other institutional investors in their buy (sell) decisions, and positive feedback trading, which refers to using information on past winners and losers and buying the past winners while selling the past losers (Lakonishok *et al.*, 1992, Nofsinger and Sias, 1999, Sias, 2004). However, evidence in the existing literature on whether institutional investors stabilize or destabilize the stock market remains mixed and inconclusive. For example, Lakonishok et al. (1992) identify a destabilizing effect from the herding and positive-feedback trading behaviours that they attribute to investment funds, while Dennis and Strickland (*op cit.*) provide results of a destabilizing effect of institutional trading behaviour on U.S. extreme market movement days. In contrast, others argue that the trading behaviours of institutional investors help to stabilize the stock market through speeding-up a necessary price-adjustment process (Wermers, 1999); by exhibiting rationale trading behaviour (Goodfellow *et al.,* 2009); by reducing stock price volatility (Li and Wong, 2010); and by reducing the extent of abnormal returns that occur during market swings (Lipson and Puckett, 2010; Tian, *et al.* (*op cit.*)).

In Chinese stock markets, as discussed above, Tian *et al.* (*op cit.*) use firm-level quarterly data on institutional ownership as a proxy for the influence of institutional trading activity. However, we are concerned that their conclusion that institutional trading acts to stabilize Chinese stock market swings ought to be re-examined on two grounds i) that there is a need for a better proxy for daily institutional trading activity and ii) that the existence of binding statutory price limits should not be ignored when examining Chinese data.

A more recent study, Chen *et al.* (2019), demonstrates the existence of destructive market behaviour on the part of large scale investors who appear to employ pump-and-dump strategies in the case of stocks that hit the regulators' upper-price-limit, i.e. achieve a price rise of 10% within a single trading day. In this chapter, we propose and utilise a different proxy international trading activity derived from the available daily cash flow data disaggregated by transaction value. More specifically, we focus on the combined net value of individual trades that exceed 1 million RMB. We then test the following hypothesis:

Hypothesis 3.1. Institutional investors tend to perform high value net buy (sell) trades in individual firms' shares on extreme-up (-down) market movement days.

The daily trading represented in these high value trades exacerbate the volatility in Chinese firm-level stock returns. Hence, if hypothesis 3.1 holds, this implies that the large value transactions conducted by institutional traders contribute to destabilising the Chinese stock markets on extreme market movement days.

3.3.2 The effects of institutional trading in the days following extreme market movement days

A notable characteristic in Chinese stock markets is that a substantial proportion of firms' shares hit the regulator's imposed price limit during extreme market movement days. The objective of regulators' in imposing price limits is to require investors take time-out to reflect on whether large movements reflect news about fundamentals or whether trading has become irrational. Statutory price limits are often used in emerging markets. However, whether the affected stock prices will continue to rise (fall) after upper (lower) price limit hit is not clear (Chen, et al., 2005; Wong et al. 2009 and Li, et al., 2014, Chen, et al., 2019).

More recent research by Chen *et al.* (2019) documents destructive market behaviour generated in response to shares hitting regulator imposed daily price limits during the period from 2012 to 2015. Specifically they find that firm-level stock prices generally continue to increase on the day following the upper limit being hit but eventually reverse over the longer run. They assert that this probably reflects the attention-grabbing effect of a price limit being hit, which then often leads active individual investors to purchase the affected firms' stocks, which they may well have never previously held (see for example, Seasholes and Wu, (2007) and Barber and Odean (2018)). On extreme market movement days it stands to reason that a greater number of firms' shares will hit the statutory price limit during the trading day, relative to the number of firms whose shares that the statutory price limits during other (non-extreme) trading days. This suggests that it will be worthwhile to investigate the effectiveness of price limits on and after extreme market movement days, and we do so through testing the following hypothesis:

Hypothesis 3.2. The prices of regular (and special treatment) stocks, after hitting the price limit of +/-10% on extreme market movement days (or +/-5% in the case of special treatment stocks), continue the same direction of movement in the days following the extreme days, although eventually these movements may be reversed in the longer run.

If empirical support is found for hypothesis 3.2, and if trading is rational, price discovery is delayed when stocks hit price limits. However, if stocks hit the statutory price limit during the trading day and trading has resulted in over-reaction relative to fundamentals, the movement is later reversed and the initial trading behaviour is destabilising. Rejection of hypothesis 3.2 would be consistent with the interpretation that the price limits 'cool-down' the kind of irrational trading behaviour that was previously driving share prices away from the level justified by their fundamentals, suggesting initial overreaction and subsequent correction.

There is a relative lack of research that examines the predictive power of institutional trading activity firm-level stock returns on the days following extreme market movement days on which price limits were hit. Nonetheless, Chen *et al.* (2019) is the first study we are aware of that examines the predictive power of large trades in individual firms' stocks for firm-level abnormal returns over various horizons from first to the 120th trading day after the price limit was hit. They find the evidence of price reversal in the days following binding upper price limits being hit and find that this effect is stronger when institutional investors are involved in high value firm-level net buy trades. Motivated by Chen *et al.* (*op cit.*), we put forward the following hypothesis to examine whether high value institutional trades in specific firms' stocks on extreme market movement days help to predict firm-level stock returns in the days following extreme market movement days.

Hypothesis 3.3. High value net trades in individual firms' stocks conducted by institutional investors on extreme market movement days are significant predictors of firm-level stock returns in the days following extreme market movement days.

Empirical support for hypothesis 3.3 would imply that high value trades by institutional investors on extreme market movement days are important in driving returns on subsequent days, while rejection of this hypothesis would provide evidence against the trades of institutional investors driving firm level stock returns in the days following extreme market movement days.

3.4 Data and measurement of variables

Our dataset includes daily market information in the form of firm-level stock returns and other firm-specific information including the our institutional trading proxy (constructed from daily cash flow data that identifies transactions by value) for every firm whose shares are listed in the Shanghai and Shenzhen stock markets. The dataset spans every trading day over the period from January 2010 to December 2017. The daily market- and firm-level information has been collected from the China Stock Market & Accounting Research Database (CSMAR), while the daily cash flow data were obtained from the RESSET (www.resset.cn) database.

3.4.1 Extreme market movement days

Following Dennis and Strickland (*op cit.*), we define extreme market movement days in the Shanghai and Shenzhen stock markets respectively as those trading days in which the absolute value of the market return exceeds two standard deviations above its full-sample mean. The thresholds surpassed in an extreme movement day, relative to the previous day's closing value of the relevant composite index, are therefore (+/-)2.90% and (+/-)3.44% in Shanghai and Shenzhen respectively. In all, our sample includes 106 extreme market movement days in Shanghai stock market, comprising 49 up- and 57 down-days, and 116 extreme market movement days in the Shenzhen stock market days, comprising 45 up- and 71 down-days. Notably, a large number (and proportion) of stocks hit the upper- (lower-) price limit in up- (down-) extreme days, particularly in Shenzhen stock market. For example, there are three extreme up days and 4 extreme down days in our sample period on which in excess of 80% of the listed firms in the Shenzhen market see their shares hit the respective upper or lower limit during trading.

All the extreme market movement days identified in our sample are listed in Appendix B, along with information on the relevant market's return expressed as the % change in the closing price on the extreme movement day relative to the closing price on the previous day; the number of stocks listed on the specific date; and information on the number of 'regular' and 'special treatment' shares. Also listed in Appendix B are the number and percentage of regular shares or special listed treatment shares that hit their respective price limits on the extreme market up days and likewise for extreme market down-days.

3.4.2 Key variables

As noted above, we obtain daily cash flow for each of the listed A-shares in the Shanghai and Shenzhen Stock Exchanges from the RESSET database. This database classifies all buy-initiated and sell-initiated trading transactions into four categories based on the value of each transaction. The categories available in the most recent data are individual transactions of i) less than 50 thousand RMB; ii) between 50 and 300 thousand RMB; iii) between 300 thousand and 1 million RMB and iv) in excess of 1 million RMB[6]. We are particularly interested in the

[6] Transactions data have been provided in the RESET database for the value ranges stated above since 2013, but the thresholds used prior to 2013 are mostly different, which restricts our focusing on transactions in excess of 1 million RMB that are available on a consistent basis for our full sample.

trading information of the largest value transactions, ie. those in excess of 1 million RMB, and use the net of buy and sell transactions in this category as a proportion of total transactions for each firm on each trading day as our proxy for daily institutional trading activity. Drawing inspiration from Chen *et al.* (*op cit.*), the key proxies we define for each listed firm, are i) NETBUY, defined as the total of buy transactions of volume[7] in excess of 1 million RMB less the total of individual sell transactions of volume in excess of 1 million RMB divided by the total value of the firm's shares outstanding and ii) NETSELL, defined as the total of sell transactions of volume in excess of 1 million RMB less the total of individual buy transactions of volume in excess of 1 million RMB, divided by the total value of the firm's shares outstanding[8].

3.4.3 Dependent variables

Consistent with Dennis and Strickland (*op cit.*) and Tian *et al.* (*op cit.*), we begin by examining the performance of individual firm's A-shares on extreme market movement days as represented by abnormal firm-level daily returns and abnormal firm-level daily turnover. Abnormal daily returns (AR) are computed from a simple CAPM model in which firm i's returns are compared to market returns over the time horizons from 250 to 50 prior to each extreme market movement day (hereafter, [*t*-250, *t*-50]). Abnormal turnover (ATURN) is the difference between turnover in firm *i*'s shares on extreme market movement days relative to the median turnover in firm i's shares over the relevant time horizon [*t*-250, *t*-50]. Turnover is defined as the trading volume on the extreme market movement day scaled by the total tradable shares outstanding.

We also examine the performance of listed firms' stocks in the days following extreme market movement days, and pay particular attention to those firms whose stocks hit the statutory price limit during trading on the extreme market movement day.

Similar to Chen *et al.* (*op cit.*), we decompose the first day return into i) CTO is the overnight component – calculated using the closing price on the extreme market movement day and the opening price on the next trading day; and ii) OTC is the 'open to close return' calculated using the opening and closing prices of the stock on first trading day after the extreme market movement day. We then construct a set of abnormal returns for each share based on several different horizons, specifically abnormal returns achieved by the close of the 1st, 2nd, 3rd, 4th

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[7] We use volume data instead of value data because using value data at times when prices are very volatile within a trading day could be a poorer representation of the percentage of stocks traded by large institutional investors.

[8] Although NETSELL is the negative value of NETBUY, the inclusion of both two variables facilitate the interpretation by identifying the positive direction of trading behaviour.

and 5th day relative to the extreme market movement day and cumulative abnormal returns from [6, 10], [11, 20], [21, 60] and [61, 120] trading days relative to on the extreme market movement day.

3.4.4 Control variables

We also include a set of control variables in our analysis, these are defined for as follows: i) SIZE, which is the natural logarithm of the market value firm *i*'s equity 50 days prior to each extreme market movement day; ii) TURNOVER, which is defined, for firm *i* on day *t*, as the ratio of shares traded to total shares outstanding; iii) VARIANCE and iv) BETA, which are defined as the residual variance and the beta of the firm's daily returns obtained from estimation of a CAPM (market model) estimated for firm *i* at time *t* over the sample [*t*-250, *t*-50] in which market returns are represented by returns in the value weighted Shanghai or Shenzhen Composite index.

These control variables are included to capture influences on daily firm-level returns that are unrelated to daily variation in institutional trading activity. The inclusion of SIZE is intended to control for the fact that i) institutional investors generally prefer to invest in large firms (e.g. Lakonishok *et al.*, 1992); and ii) firm size is documented as a risk factor i.e. can capture a dimension of systematic risk (see Banz, 1981; Fama and French, 1993). TURNOVER is included since institutional investors are generally found to have a preference for highly liquid stocks (Falkenstein, 1996; Gompers and Metrick, 2001). Relative to retail (individual) investors, institutional investors tend to be considered as informed investors (e.g. Wermers, 2000; Li and Wang, 2010), on this basis institutional holdings ae expected to be negatively related to firm-level information asymmetry. The inclusion of VARIANCE is intended to capture the likelihood that institutional investors are averse to investing in stocks that experience fewer idiosyncratic shocks (Falkenstein, 1996). BETA is included as an additional, commonly used, proxy for systematic risk. If institutional investors have a preference for holding stocks with a high beta then regressions might otherwise be subjected to omitted variable bias.

3.4.5 Descriptive statistics

Table 3.1 provides the descriptive statistics for the key variables used in our analysis of extreme market movement days in the Shanghai and Shenzhen markets. Extreme market movement days are separated into up- or down- extreme days according to the sign of market return. In the Shanghai market we capture a total of 38,740 firm-day observations on extreme up-days, and a larger number of firm-day observations, 45,411 on extreme-down days. The distribution shows greater asymmetry toward the downside in the Shenzhen stock market over our sample period. There are a total of 48,173 firm-day observations on extreme up-days, which is far fewer than the 76,972 firm-day observations on extreme- down days.

The sign of NETBUY (NETSELL) is of particular interest in this study since this reflects the trading directions observed in the cash flow data on the of largest transactions by value, which is our proxy for the trading behaviour of institutional investors[9]. The values of NETBUY (NETSELL) have been multiplied by 100 for convenience. The means and median firm-level NETBUY and NETSELL on extreme-up and extreme-down days are all positive across both markets, suggesting that, on average, the largest individual transactions on extreme-up dates tend to institutional trader instigated purchases and tend to be institutional trader instigated sales on extreme-down days. The mean of NETBUY (after multiplying by 100) is 0.191 (0.258) on Shanghai (Shenzhen) extreme-up days, much higher than the mean of NETSELL, which is 0.024 (0.008) on Shanghai (Shenzhen) extreme-down days. This is suggestive of large trades instigated by institutional investors having a more pronounced effect in exacerbating extreme movements on extreme-up days relative to extreme- down days[10].

Regarding the discernible differences in four control variables in our study between two markets, Table 3.1 reports the statistics that reveal SIZE is greater for firms on average in the Shanghai stock market relative to Shenzhen, while TURNOVER, VARIANCE and BETA tend to be lower.

[9] As suggested by Tian *et al.* (2018), institutional investors in Chinese stock market can be categorized into four groups, which are Mutual Funds, Qualified Foreign Institutional Investors (QFII), Financial Institutions and ‘other’ Institutional Investors. During our sample period, the ownership of institutional investors accounts for, on average, 37.7% in all shares outstanding. The ownerships of mutual funds and QFII account for 6.7% and 0.2% respectively. The ownership of ‘other’ Institutional Investors, including such as legal person share and pension fund, accounts for 28.7%, see Tian *et al.* (2018) in more detailed discussion.

[10] On average, across all extreme market movement days in our sample, the proportions of institutional trading, including both buy-initiated and sell-initiated trades in extreme markets, are 24.65% (17.16%) on Shanghai (Shenzhen) stock exchanges.

Table 3.1: Descriptive statistics

The table records descriptive statistics of key variables used in our analysis of extreme market movement days in the Shanghai and Shenzhen stock markets (where extreme movement days are defined as those on which the absolute market return exceeds of two standard deviations above mean). RETURN is the stock return on extreme day and AR is abnormal stock return calculated from a simple CAPM model. NETBUY (NETSELL) refer to net values of large individual buy (sell) trades – our proxy for institutional trading behaviour discussed in Section 3.3.2 - its values have been multiplied by 100 for convenience. SIZE, TURNOVER, BETA and VARIANCE are control variables, as defined in section 3.3.4.

	Mean	Min	25th	Median	75th	Max	Std.
Panel A: Shanghai extreme-up days					(number of observations 38,740)		
RETURN	0.041	-0.100	0.021	0.037	0.059	0.106	0.031
AR	0.003	-0.159	-0.012	-0.002	0.020	0.109	0.031
NETBUY	0.191	-27.209	0.000	0.037	0.199	27.473	0.913
NETSELL	-0.191	-27.473	-0.199	-0.037	0.000	27.209	0.913
SIZE	22.543	19.081	21.736	22.355	23.133	28.374	1.185
TURNOVER	0.032	0.000	0.012	0.023	0.041	0.523	0.031
BETA	1.080	-0.545	0.838	1.116	1.338	2.687	0.361
VARIANCE	0.072	0.002	0.034	0.057	0.095	2.059	0.062
Panel B: Shanghai extreme-down days					(number of observations 45,411)		
RETURN	-0.056	-0.101	-0.093	-0.055	-0.033	0.101	0.037
AR	-0.009	-0.105	-0.03	-0.008	0.01	0.232	0.036
NETBUY	-0.024	-10.324	-0.167	-0.038	0.008	23.447	0.658
NETSELL	0.024	-23.447	-0.008	0.038	0.167	10.324	0.658
SIZE	22.556	19.081	21.736	22.388	23.185	28.429	1.212
TURNOVER	0.032	0.000	0.012	0.023	0.042	0.502	0.032
BETA	1.074	-0.275	0.833	1.104	1.342	3.971	0.353
VARIANCE	0.083	0.002	0.042	0.067	0.105	59.354	0.286
Panel C: Shenzhen extreme-up days					(number of observations 48,173)		
RETURN	0.052	-0.1	0.033	0.047	0.069	0.102	0.028
AR	0.002	-0.192	-0.014	-0.002	0.016	0.134	0.026
NETBUY	0.258	-15.405	0.000	0.080	0.287	21.932	0.67
NETSELL	-0.258	-21.932	-0.287	-0.080	0.000	15.405	0.67
SIZE	22.01	18.983	21.32	21.977	22.67	26.001	1.053
TURNOVER	0.041	0.000	0.017	0.031	0.054	0.604	0.036
BETA	1.226	-1.291	1.046	1.239	1.418	2.329	0.263
VARIANCE	0.117	0.003	0.043	0.073	0.112	375.562	3.295
Panel D Shenzhen extreme-down days					(number of observations 76,972)		
RETURN	-0.059	-0.101	-0.096	-0.06	-0.037	0.102	0.037
AR	-0.001	-0.129	-0.021	-0.004	0.014	0.265	0.032
NETBUY	-0.008	-13.74	-0.144	-0.012	0.024	27.578	0.655
NETSELL	0.008	-27.578	-0.024	0.012	0.144	13.74	0.655
SIZE	21.94	18.817	21.215	21.919	22.62	26.004	1.062
TURNOVER	0.038	0.000	0.015	0.029	0.05	0.591	0.036
BETA	1.196	-2.189	1.016	1.197	1.383	5.611	0.268
VARIANCE	0.098	0.003	0.038	0.063	0.099	353.624	1.881

3.5 Methodology

3.5.1 Analysis of extreme market movement days

Our main hypothesis is that the institutional investors exacerbate the volatility of the Chinese stock markets on extreme market movement days. We draw on the set-up used in Dennis and Strickland (*op cit.*) but use our preferred proxy for institutional trading derived from daily cash flow data on transactions in excess of 1 million RMB. We investigate the effects of institutional trading on abnormal returns and on abnormal turnover on extreme market movement days in each of the Shanghai and Shenzhen markets.

Institutional investors tend to conduct net buying trading on extreme market up days and net selling trading behaviour on extreme market down days, we further use NETBUY and NETSELL in up and down extreme days respectively to test the Hypothesis 3.1. We then specify the following regressions for all extreme market up days using a Fama and MacBeth (1973) approach:

$$AR_i = \gamma_0 + \gamma_1 NETBUY_i + \gamma_2 SIZE_i + \gamma_3 TURNOVER_i$$

$$+\gamma_4 VARIANCE_i + \gamma_5 BETA_i + \varepsilon_i, \qquad (3\text{-}1)$$

$$ATURN_i = \gamma_0 + \gamma_1 NEYBUY_i + \gamma_2 SIZE_i + \gamma_3 VARIANCE_i + \varepsilon_i, \qquad (3\text{-}2)$$

where, AR_i are abnormal returns, and $ATURN_i$ abnormal turnover, of firm i on extreme market up days; $NETBUY_i$ is institutional traders' high value net purchases as a proportion of the total value of firm *i*'s tradable shares outstanding. All other variables are as defined as set out in section 3.3.3.

We then specify the regression estimated for all firms, over all extreme market down days, using the NETSELL variable as

$$AR_i = \gamma_0 + \gamma_1 NETSELL_i + \gamma_2 SIZE_i + \gamma_3 TURNOVER_i$$

$$+\gamma_4 VARIANCE_i + \gamma_5 BETA_i + \varepsilon_i, \qquad (3\text{-}3)$$

$$ATURN_i = \gamma_0 + \gamma_1 NEYSELL_i + \gamma_2 SIZE_i + \gamma_3 VARIANCE_i + \varepsilon_i, \qquad (3\text{-}4)$$

where, AR_i are abnormal returns and $ATURN_i$ abnormal turnover of firm i on extreme down days; $NETSELL_i$ is institutional traders' high value net purchases as a proportion of the total value of firm *i*'s tradable shares outstanding and all other variables are defined as set out in section 3.3.3.

3.5.2 Post-extreme market movement day analysis

We now turn to explaining how we test the whether or not stocks that hit the price limit during extreme market movement days generally continue to experience significant positive (negative) returns on subsequent trading days (Hypothesis 3.2), and whether they are more prone to do so than stocks that experience price movements within the permitted limits on extreme market movement days.

Given that different price limits that apply, we analyse regular and special treatment stocks separately. In what follows we describe our approach to the analysis of regular stocks. We first group all stock-day observations into 9 categories based on the magnitude of day-0 excess returns i.e. the magnitude of the return recorded on each extreme market up day and on each extreme market down day. In the case of up days, the first group consists of stocks that hit the price limit of +10%; the next group consists of stocks that rise by at least 9% but less than 10%; and four further groups capture stocks that move within one percentage point bands. Three more bands capture stocks that rise by <5% or fall by up to 5%; those that fall by more than 5% but by less than 10%; and finally, those that hit the lower limit. For trading following extreme market down days we look in most detail at the price falls: the first group consist of stocks that hit the lower limit of -10%; the next, those that fall by at least 9% but less than 10%, then those that fall by at least 8% but less than 9% and so on. The final three groups capture stocks that see their prices change by up to 5% in either direction; that rise by at more than 5% but less than 10%; and finally those that hit the upper limit on extreme market down days. Our next step is to decompose the first day abnormal return for each group of stock-days into i) CTO (i.e. overnight return), calculated from the closing price on the extreme market movement day and the opening price on the following trading day and ii) OTC, which refers to the return calculated from the opening and closing price on the first trading day following the extreme market movement day. We also report the abnormal returns for the stocks in each group over the 2nd, 3rd, 4th and 5th trading days follow each extreme market movement day and cumulative abnormal returns over days 6 to 10, 11-20, 21-60 and 61-120. The results of this analysis will allow us to infer whether or not abnormal returns continue to increase (decrease) in the days following extreme market up (down) days, and will allow us to check whether or not there are clear differences in the subsequent direction of movements in abnormal returns for those stocks that hit a statutory price limit during trading on the extreme market movement day as distinct from those stocks that experienced price changes within the permitted limits during trading on extreme days.

Finally, our investigation turns to of hypothesis 3.3, whether the large net trades conducted by institutional investors on extreme market movement days are significant predictors of subsequent movements in firm level abnormal stock returns. Following Chen *et al.* (*op cit.*) we pool all stock-day observations in our sample then analyse regular and special treatment stocks separately due to differences in the applicable price limits, though while they look at daily data for both markets over the full period 2012-2015, our analysis focuses on extreme market up and down days over the period 2010-2017 and is conducted separately for the Shanghai and Shenzhen stock markets. We set out the details of our analysis on regular stocks below while the analysis of special treatment stocks is set out in Appendix C.

Our pooled regression framework is drawn from Chen et al. (2019), estimated for regular stocks on the extreme market up days and for extreme market down days are specified as follows:

$$\begin{aligned} RET_{i,t+n\rightarrow t+m} = {} & \gamma_0 + \gamma_1 UPPER_{i,t} + \gamma_2 NETBUY_{i,t} + \gamma_3 UPPER_{i,t} * NETBUY_{i,t} \\ & + \gamma_4 EIGHT_{i,t} + \gamma_5 EIGHT * NETBUY_{i,t} + \gamma_6 SIX_{i,t} + \gamma_7 SIX * NETBUY_{i,t} \\ & + \gamma_8 FOUR_{i,t} + \gamma_9 FOUR * NETBUY_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} TURNOVER_{i,t} \\ & + \gamma_{12} VARIANCE_{i,t} + \gamma_{13} BETA_{i,t} + \varepsilon_{i,t} \end{aligned}$$

$$\text{where } n, m \, \epsilon \{1,2,3,4,5,10,20,60,120\} \qquad (3\text{-}5)$$

$$\begin{aligned} RET_{i,t+n\rightarrow t+m} = {} & \gamma_0 + \gamma_1 LOWER_{i,t} + \gamma_2 NETSELL_{i,t} + \gamma_3 LOWER_{i,t} * NETSELL_{i,t} \\ & + \gamma_4 NEIGHT_{i,t} + \gamma_5 NEIGHT * NETSELL_{i,t} + \gamma_6 NSIX_{i,t} \\ & + \gamma_7 NSIX * NETSELL_{i,t} + \gamma_8 NFOUR_{i,t} + \gamma_9 NFOUR * NETSELL_{i,t} \\ & + \gamma_{10} SIZE_{i,t} + \gamma_{11} TURNOVER_{i,t} + \gamma_{12} VARIANCE_{i,t} + \gamma_{13} BETA_{i,t} + \varepsilon_{i,t} \end{aligned}$$

$$\text{where } n, m \, \epsilon \{1,2,3,4,5,10,20,60,120\} \qquad (3\text{-}6)$$

where, $RET_{i,t+n\rightarrow t+m}$ is the dependent variable, defined as the market-adjusted abnormal returns for stock *i* on days 1, 2. 3. 4 and 5 (previously denoted $AR_{i,t+n,t+n+1}$), and cumulative abnormal returns over various time windows subsequent to extreme market up day *t*, specifically over days [6, 10], [11, 20], [21, 60] and [61, 120].

$UPPER_{i,t}$ is a dummy variable which is equal to one if the price of stock *i* on day *t* rises by 10% during the trading, so the upper price limit is hit, and is zero otherwise. $LOWER_{i,t}$ is a dummy variable which is equal to one if the price of stock *i* on day *t* falls by 10% during trading, so the lower price limit is hit, and is zero otherwise. In order to allow comparison of price dynamics on days following extreme market movements of stocks that hit price limits with those of stocks that did not hit the price limits, we also include three further dummy variables in each regression, for equation (3-5) we define $EIGHT_{i,t}$, $SIX_{i,t}$ and $FOUR_{i,t}$ which set to 1 for stocks that experience within limit price rises in three 2% intervals (<10% but ≥8%, <8% but ≥6%, <6% but ≥4% respectively) and zero otherwise, while $NEIGHT_{i,t}$, $NSIX_{i,t}$ and $NFOUR_{i,t}$ for equation (3-6), for similarly defined within limit price falls. All other variables are defined as previously. In addition, the standard errors have been corrected for clustering at the firm level by using heteroscedasticity-robust standard errors.

Our key interest is in the interaction term UPPER * NETBUY on extreme market up days and LOWER * NETSELL on extreme market down days. More specifically, significant positive estimates of the coefficients on this interaction term, γ_3 in Equation (3-5) (Equation (3-6)), would be consistent with a stronger delay to the price adjustment of stocks being generated in the days following extreme market movement days, for those stocks that hit the upper-price-limit (lower-price-limit) and experienced high value net buy (net sell) transactions on the extreme market movement day.

3.6 Results

3.6.1 Extreme market movement days

Table 3.2 presents the results of estimation of equations (3-1) to (3-4) for each of the Shanghai and Shenzhen stock markets where the sample includes all listed companies and every extreme market up or down movement day over the years 2010-2017. The equations are estimated using the Fama-MacBeth (1973) approach. We focus on the estimated impact of institutional trading behaviour on firm-level stock returns on extreme market up (down) days. As explained previously, institutional trading is represented by net of large net buy (sell) transactions in individual firms' stocks as a percentage of the total value of the firm's stocks outstanding. The key coefficients of interest in columns (1) and (3) relate to the estimated relationship between firm-level abnormal stock returns and large net buy transactions on extreme market up days in each of the Chinese stock markets, while columns (2) and (4) similarly focus on the relationship between firm-level abnormal stock returns and large net sell transactions on extreme market down days. In each case the coefficient on the large net buy (net sell) transactions has the expected positive (negative) sign and is significant at the 1% level. More specifically, the coefficient of NETBUY (NETSELL) in Shanghai stock market is 1.898 (-2.809), which implies that a 1% increase in the net value of large transactions as a share of total tradable shares outstanding is associated with an increase (decrease) of approximately 1.9% (2.8%) in abnormal stock returns. From these results we infer that the large trades attributable to institutional investors have a significant destabilizing effect on extreme market movement days, and further that the estimated destabilising greater in the Shanghai stock market relative to Shenzhen stock market. This finding is contrary to the estimated stabilizing effect of institutional ownership reported in Tian *et al.* (*op cit.*), although we stress that their results rely on quarterly data on institutional ownership to proxy institutional trading activity, while our results rely on our more timely proxy for daily institutional trading activity. It seems likely that their quarterly proxy is simply not able to capture the shorter-term variation in institutional trading behaviour and that this distorts their results. This finding is also supportive for the view that firms with higher retail investor attention tend to have a lower future stock price crash risk (Wen *et al.*, 2019).

Column (5), (6), (7) and (8) in table 3.2 report the estimated impacts of institutional trading on abnormal turnover of firms' stocks on extreme market movement days. The results indicate that large purchase transactions attributed to institutional investors (NETBUY) significantly exacerbate abnormal turnover on extreme market up days whereas large net sell transactions (NETSELL) significantly decrease abnormal turnover on extreme market down days. More specifically, one percent increase in NETBUY generates, on average, an increase of approximately 1.981 (1.939) percent in abnormal turnover for shares listed in the Shanghai (Shenzhen) market on extreme market up days, while on extreme market down days, a one percent increase of NETSELL tends to decrease abnormal turnover by approximately 1.419 (1.137) percent in the Shanghai (Shenzhen) market.

Our finding that institutional trading activity exacerbates abnormal turnover on extreme market up days, yet decreases abnormal turnover on extreme market down days is perhaps surprising, although a plausible explanation that draws on the existing literature is that the actions of institutional traders on extreme market down days can often instigate panic selling by large numbers of individual (retail) investors, potentially leading more shares to hit the regulator imposed downward price limits during the trading day; this then results prevents any further transactions that would depress the price of a limit- hitting stock any further until the next trading day. Such temporary suspensions in trading decrease the liquidity of the affected stocks (e.g. Kim and Rhee, 1997) which could explain the negative impact on abnormal turnover. More generally, the potential for regulator imposed price limits to conflate the impacts of institutional trading on and following extreme market movement days motivates our analysis of post-extreme day performance.

Table 3.2: Abnormal returns and abnormal turnover, Shanghai and Shenzhen stock market

This table reports regression results used to investigate the impacts of large trades conducted by institutional investors on abnormal stock returns and abnormal turnover respectively. The sample includes of all A-shares listed on the Shanghai and Shenzhen Stock Exchanges and all extreme market up or down movement days over the years 2010 to 2017. Results are for estimation of Equations (3-1)-(3-4) which are Fama-MacBeth (1973) style regressions. The dependent variables are stock abnormal return (AR) on extreme day, calculated from market model over [*t*-250, *t*-50]; and abnormal turnover (ATURN), calculated from difference between turnover on extreme days and the median turnover upon [*t*-250, *t*-50]. The key explanatory variables are NETBUY and NETSELL which are our proxies for institutional trading behaviour, referring to the net of large buy and sell transactions that take place on extreme market movement days. All variables are defined in section 3.3, t-values are shown in parenthesis. "***", "**" and "*" represent statistical significance at 1%, 5% and 10% levels respectively.

	Dependent variables: Abnormal returns				**Dependent variables: Abnormal turnover**			
	Shanghai stock market		Shenzhen stock market		Shanghai stock market		Shenzhen stock market	
	Up	Down	Up	Down	Up	Down	Up	Down
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
NETBUY	1.898^{***}		1.406^{***}		1.981^{***}		1.939^{***}	
	(10.0)		(9.54)		(19.0)		(13.2)	
NETSELL		-2.809^{***}		-2.529^{***}		-1.419^{***}		-1.137^{***}
		(-11.8)		(-16.2)		(-10.2)		(-6.88)
SIZE	0.000	0.003^{***}	-0.001^{**}	0.003^{***}	-0.001^{***}	-0.001^{**}	-0.001^{*}	-0.001
	(0.20)	(4.99)	(-2.19)	(6.18)	(-3.27)	(-2.56)	(-1.78)	(-1.05)
TURNOVER	-0.033^{*}	0.128^{***}	-0.046^{***}	0.084^{***}				
	(-1.86)	(5.72)	(-3.38)	(4.25)				
VARIANCE	0.007	-0.046^{***}	0.012^{*}	-0.025^{***}	-0.047^{***}	-0.060^{***}	-0.065^{***}	-0.052^{***}
	(0.84)	(-5.00)	(1.70)	(-3.45)	(-4.65)	(-6.21)	(-6.09)	(-6.25)
BETA	-0.022^{***}	0.023^{***}	-0.021^{***}	0.026^{***}				
	(-12.3)	(8.74)	(-11.7)	(12.3)				
Constant	0.020	-0.094^{***}	0.052^{***}	-0.109^{***}	0.040^{***}	0.041^{***}	0.032^{*}	0.022
	(1.14)	(-6.23)	(3.97)	(-8.41)	(3.71)	(3.20)	(1.90)	(1.59)
No. Obs.	38,740	45,411	48,173	76,972	38,740	45,411	48,173	76,972
R^2	0.595	0.510	0.397	0.333	0.445	0.413	0.382	0.352

3.6.2 Post-extreme day performance

Tables 3.3 and 3.4 report the estimated abnormal returns and cumulative abnormal returns of regular stocks over periods that follow each of the extreme market movement days that occurred between 2010 and 2017, for all stocks listed on the Shanghai and Shenzhen stock exchanges respectively. As explained in section 3.4.2, we group the stocks by the magnitude of their day 0 price changes, i.e. the price change recorded on the extreme market movement day. This allows us to explore whether subsequent price dynamics differ for stocks that hit price limits during trading relative to those stocks that experience lesser, within limit, price changes on the extreme market movement days. There may bring concerns that some price-limit-hitting stocks continue to hit the price limit on the next day, the evidence of which is more frequent during the market crash period of 2015-2016. Similar to Chen et al. (2019), we consistently record abnormal returns in post extreme days even when price limit is hit again. Moreover, if the limit is hit on two consecutive extreme days both will independently be recorded as price limit cases in extreme movement days.

The first row records abnormal returns and cumulative abnormal returns on days subsequent to extreme market movement days for those regular stocks that hit the 10% upper price limit during trading on the extreme market movement day. It is striking that abnormal returns for this group of stocks continue to be positive and significant over horizons of up to two subsequent days in both markets. This pattern is not evident in stocks that record substantial within limit rises on the extreme up days (compare Panel A row 1 with rows 2 onwards). More specifically, the first row of Panel A in Table 3.3 (Table 3.4) report the close-to-open (CTO) return is on average 2.64% (2.59%), and abnormal returns continue to be positive during trading on the first day following the extreme movement day, on average at 1.52% (0.8%). Our results further indicate that stock prices continue to rise by 1.31% (0.46%) on average on the second subsequent day of trading. We can see that a pattern of partial price reversal occurs on days 3 and 4 but note that the estimated cumulative abnormal returns show no evidence of significant longer run price reversal shown (as indicated in the absence of significant negative cumulative abnormal returns in the rightmost columns of Panel A).

Likewise, the abnormal returns of regular stocks that hit the lower price limit during trading on extreme market down days in both markets continue to be negative and significant for horizons of up to two subsequent days, but again there is no clear pattern in the subsequent abnormal returns of shares that recorded lesser (within-limit) falls on the extreme market movement days (compare Panel B final row with the rows above).

More specifically, the final rows of Panel B in Tables 3.3 and 3.4 show the pattern of subsequent abnormal returns and cumulative abnormal returns for those stocks that hit the lower price limit on during trading during on extreme market down days in the Shanghai and Shenzhen markets respectively. The close-to-open return (CTO) of -2.49% (-2.92%) indicates significant drops in the stock prices when the market opens for trading on the first day following the extreme down day. A more moderate average drop of -0.24% (-0.49%) is recorded during trading as indicated in the open-to-close (OTC) return. These groups of stocks continue to record negative abnormal returns on average on days 2 through to 4 in the Shanghai market (though only to day 2 for the Shenzhen market).

It is notable that over the longer term there is evidence of subsequent price reversal of the stocks that hit downward price limits during trading on extreme market down days. For example, the table records significant positive cumulated abnormal returns over the horizon [61, 120] days of on average 1.86% (2.09%) in the Shanghai and Shenzhen samples. In contrast there is no evidence of significant longer run price reversal for stocks that hit upper price limits during trading on extreme market up days, compare the significant positive coefficients take from the rightmost columns of Panel B with the more variable figures and particularly the lack of any significant negative coefficients in the rightmost columns in Panel A.

That the patterns referred to above are clear among shares that hit statutory price limits during extreme market movement days but are not evident among stocks that traded within the price limits provides clear evidence of the importance of stocks hitting binding price limits in determining post-extreme day performance. These results are similar to those reported in Chen *et al.* (*op cit*) although our results indicate more pronounced price dynamics of price limit hitting stocks on days subsequent to extreme market movement days than those that they reported. However, it is important to note that Chen *et al.* (i) focus on all stock-days that recorded large upward price movements, rather than on extreme market movement days; ii) examine only data for Shenzhen A shares; iii) use a different proxy for net trading behaviour of large investors with stock balances above 10 million RMB; and iv) investigate these movements for stock-day observations over a somewhat shorter window from 2012-2015. We suggest that the main explanation for the differences in our results is that binding price limits have a greater influence on subsequent price dynamics after extreme market movement days than on stock-days in which large upward movements are recorded in individual stock prices.

Our comparable analysis of special treatment stocks is reported in Appendix C, in Tables C.1 and C.2. Note first that the number of observations used in this analysis is necessarily far smaller, which is likely to impact on the precision of the estimates. Nonetheless, following extreme market up days, those special treatment shares that hit the upper price limit in trading show significant and positive subsequent abnormal returns (from open to close on the day following the extreme movement day and on the subsequent day in the Shanghai market, and at the opening of trading following the extreme market day and for the next two days in the Shenzhen market. Likewise stocks that hit lower price limits on extreme market down days show negative CTO returns further negative abnormal returns in several subsequent days of trading in both the markets, more persistently so than for regular stocks. Cumulative abnormal returns indicate no significant price reversals in the case of the special treatment stocks that hit upper price limits during trading on extreme market up days, and only the Shenzhen market data gives evidence of a small longer run price reversal among stocks that hit the lower price limit during extreme market down days.

3.6.3 Is institutional trading a significant predictor of subsequent abnormal returns?

In this subsection we examine whether the large net buy (net sell) transactions conducted by institutional investors on extreme market movement days have predictive power for subsequent abnormal stock returns. Panel A in Tables 3.5 and 3.6 reports the results of estimating equations (3-5) and (3-6) for regular stocks following extreme market up days in the Shanghai and Shenzhen stock markets respectively. Panel B in each table reports equivalent results for extreme market down days.

The key variable of interest in Panel A is the interaction term UPPER*NETBUY. That this term attracts significant positive coefficients in the abnormal returns regressions in the first three columns indicates strong support for Hypothesis 3.3 that the high value net trades in individual firms' stocks conducted by institutional investors on extreme market movement days are significant predictors of continued positive firm-level abnormal stock returns in each of the next three (four) days following the extreme market movement days in the case of stocks that hit the 10% upper price limit on the extreme market movement day in the Shanghai and Shenzhen markets respectively. Note that the significant negative coefficients on NETBUY in the Shenzhen results act to partially offset the effect of UPPER*NETBUY, but not sufficiently to result in price reversal. These results contrast with those reported in table 3.4 of Chen *et al*. (op cit) p258: they estimated negative coefficients on similar interaction terms for firm-day samples over the period 2012-2015 and concluded that there was evidence of strong price reversal, associated with greater net buys of institutional investors after upper-price limit hits. We again suggest that the main explanation for these differences in results is that binding price limits have a distinctive influence on subsequent price dynamics after extreme market movement days as opposed to on (the wider range of) days subsequent to individual stocks hitting the upper price limit. The distinction is likely to derive from the fact that high value institutional trades in the shares of specific companies that take place on extreme market movement days are more likely to attract the attention of (less informed) retail investors.

The fact that clear patterns are absent in the subsequent firm level abnormal returns for those stocks that recorded within limit returns on extreme market movement days again supports our conclusion that distinctive and significant subsequent price dynamics look to be concentrated in those stocks that hit the upper price on the extreme market movement days.

Turning to our analysis of abnormal returns in regular stocks following extreme market down days, we find clear results in the Shenzhen market (Panel B in Table 3.6) in that estimated coefficients on the interaction term LOWER*NETSELL are positive and significant in the abnormal returns regressions for three trading days following the extreme market down days in the Shenzhen market. This is consistent with significant price reversal for stocks that hit the lower price limit during trading on the extreme down days which is positively associated with the share of high value net sell transactions attributed to institutional investors on the extreme market down day. However, the corresponding estimates for the Shanghai stock market do not show any clear pattern. Nonetheless, the coefficient of NETSELL in the Shenzhen regressions on the first subsequent day of trading is 0.167, implying that an increase in the share of high value net sell transactions by institutional investors is associated with an average increase of 0.167% in the abnormal returns of stocks in the first trading day that follows an extreme market down day. Our interpretation of these results is that large net sell transactions on extreme market down days mainly reflect panic selling and help to predict positive abnormal returns in subsequent days.

Table 3.3: Post-extreme day performance of regular stocks in the Shanghai stock market

The table records log abnormal returns and logged cumulative abnormal returns at various horizons following extreme market movement days. The sample includes all stocks listed in Shanghai stock market during 2010 to 2017. Stocks are separated into groups according to the extent of the price rise/fall recorded on the extreme market movement day (day 0), as indicated in the first column. The numbers of shares in each group are indicated in the far right column (Obs.). CTO refers to the return calculated from the closing price on day 0 and the open price on the subsequent trading day, day 1. OTC refers to the return calculated from the opening and closing price on day 1. Columns headed day 2, 3, 4 and 5 refer to the abnormal return on the 2nd, 3rd, 4th and 5th day relative to day 0. [6, 10], [11, 20], [21, 60] and [61, 120] refer to the cumulative abnormal return from time window over 6th to 10th, 11th, to 20th, 21st to 60th, and 61st to 120th day relative to day 0. Abnormal returns are calculated using stock's daily return minus the expected return from a market model. "***", "**" and "*" represent statistical significance at 0.1%, 1% and 5% levels respectively.

	CTO	OTC	Day 2	Day 3	Day 4	Day 5	[6, 10]	[11, 20]	[21, 60]	[61, 120]	Obs.
Panel A (Abnormal) returns of regular stocks in Shanghai stock market following extreme market up days											
Upper Hit	2.64%***	1.52%***	1.31%***	-0.78%***	-0.41%***	1.06%***	2.06%***	-2.94%***	1.69%***	0.06%	3300
[9%, 10%)	-0.06%	-0.16%	-0.45%**	-0.24%	0.51%***	0.54%***	0.49%	-5.00%***	1.09%*	0.52%	1050
[8%, 9%)	-0.59%***	-0.38%**	-1.08%***	-0.39%**	0.73%***	-0.02%	0.31%	-3.14%***	1.83%***	-0.99%**	1139
[7%, 8%)	-0.27%***	0.30%**	-0.53%***	-0.36%***	0.38%***	-0.04%	0.17%	-2.61%***	1.03%**	-0.66%*	1542
[6%, 7%)	-0.25%***	0.49%***	-0.47%***	-0.06%	0.02%	-0.18%*	0.55%*	-1.42%***	1.22%***	0.05%	2310
[5%, 6%)	-0.21%***	0.80%***	-0.30%***	0.17%**	-0.01%	0.07%	1.23%***	-0.86%***	1.02%***	0.87%***	3249
[-5%, 5%)	-0.16%***	0.55%***	0.03%	0.05%**	-0.42%***	0.08%***	1.22%***	0.29%***	1.76%***	0.95%***	24770
(-10%,-5%)	-1.35%***	0.80%	-2.21%***	-2.22%***	-3.2%***	-0.12%	-4.03%	-3.38%	2.74%	-1.96%	64
Lower Hit	-7.54%***	5.43%**	-5.52%***	-4.28%**	-5.01%**	-1.33%	-8.78%	-5.69%	3.27%	3.68%	18
Panel B (Abnormal) returns of regular stocks in Shanghai stock market following extreme market down days											
Upper Hit	0.09%	1.53%**	-0.22%	-0.65%	-1.11%**	-0.82%*	2.02%	-1.55%	-1.76%	3.5%**	180
[5%, 10%)	-2.18%***	2.01%***	0.01%	-1.19%***	-0.87%**	-1.33%***	0.18%	-0.56%	0.41%	1.10%	280
[-5%, 5%)	-0.51%***	0.67%***	-0.17%***	-0.17%***	-0.50%***	-0.30%***	0.76%***	0.37%***	0.72%***	1.19%***	18362
[-6%, -5%)	-0.46%***	0.23%***	0.00%	-0.15%**	-0.42%***	-0.09%*	0.59%**	0.76%***	0.85%***	1.11%***	4139
[-7%, -6%)	-0.56%***	0.25%***	-0.09%	-0.21%***	-0.45%***	-0.08%	0.65%**	0.31%	0.38%*	1.06%***	3389
[-8%, -7%)	-0.66%***	0.42%***	-0.05%	-0.47%***	-0.42%***	0.09%	0.86%**	0.66%*	0.8%***	0.81%***	2768
[-9%, -8%)	-0.45%***	0.3%**	-0.07%	-0.70%***	-0.51%***	0.34%***	0.71%*	0.8%**	0.65%**	0.91%***	2368
(-10%, -9%)	-0.66%***	0.63%***	-0.02%	-0.42%***	-0.39%***	0.04%	0.76%**	0.61%*	0.11%	1.28%***	3528
Lower Hit	-2.49%***	-0.24%**	-0.86%***	-0.94%***	-0.81%***	-1.25%***	-3.56%***	2.93%***	-0.13%	1.86%***	8678

Table 3.4: Post-extreme day performance of regular stocks in Shenzhen stock market

The table records log abnormal returns and logged cumulative abnormal returns at various horizons following extreme market movement days. The sample includes all stocks listed in Shenzhen stock market during 2010 to 2017. Stocks are separated into groups according to the extent of the price rise/fall recorded on the extreme market movement day (day 0), as indicated in the first column. The numbers of shares in each group are indicated in the far right column (Obs.). CTO refers to the return calculated from the closing price on day 0 and the open price on the subsequent trading day, day 1. OTC refers to the return calculated from the opening and closing price on day 1. Columns headed day 2, 3, 4 and 5 refer to the abnormal return on the 2nd, 3rd, 4th and 5th day relative to day 0. [6, 10], [11, 20], [21, 60] and [61, 120] refer to the cumulative abnormal return from time window over 6th to 10th, 11th, to 20th, 21st to 60th, and 61st to 120th day relative to day 0. Abnormal returns are calculated using stock's daily return minus the expected return from a market model. "***", "**" and "*" represent statistical significance at 0.1%, 1% and 5% levels respectively.

	CTO	OTC	Day 2	Day 3	Day 4	Day 5	[6, 10]	[11, 20]	[21, 60]	[61, 120]	Obs.
Panel A (Abnormal) returns of regular stocks in Shenzhen stock market subsequent to extreme market up days											
Upper Hit	2.59%***	0.80%***	0.46%***	-0.15%**	-0.09%	0.44%***	1.46%***	0.36%	1.41%***	1.63%***	5925
[9%, 10%)	-0.15%	-0.40%***	-0.41%***	-0.38%***	0.43%***	0.01%	1.56%***	0.51%	1.19%**	1.12%**	1460
[8%, 9%)	-0.51%***	0.02%	-0.27%***	-0.25%**	0.46%***	0.00%	1.91%***	0.67%	1.53%***	0.84%**	1848
[7%, 8%)	-0.57%***	0.30%***	-0.24%***	0.09%	0.35%***	0.04%	2.68%***	0.96%***	1.87%***	0.48%*	2612
[6%, 7%)	-0.24%***	0.60%***	-0.10%*	-0.03%	0.16%***	-0.01%	2.15%***	0.92%***	1.28%***	1.11%***	3868
[5%, 6%)	-0.11%***	0.74%***	-0.07%	-0.01%	0.16%***	0.15%***	1.98%***	0.96%***	1.39%***	1.27%***	5772
[-5%, 5%)	-0.14%***	0.81%***	-0.09%***	-0.11%***	-0.07%***	-0.03%*	1.46%***	1.12%***	1.43%***	1.46%***	25993
(-10%,-5%)	-2.06%***	-1.11%	-2.13%***	-1.93%**	-3.01%***	-0.37%	-3.19%	-0.17%	3.20%	0.18%	44
Lower Hit	-9%***	1.67%*	-5.42%***	-3.54%***	-1.04%	-1.00%	2.58%	-0.68%	1.60%	2.92%*	56
Panel B (Abnormal) returns of regular stocks in Shenzhen stock market subsequent to extreme market down days											
Upper Hit	-0.14%	3.25%***	0.89%**	0.33%	0.30%	-0.79%***	1.05%	2.79%**	1.48%*	2.31%***	393
[5%, 10%)	-1.98%***	2.65%***	-0.71%***	-0.67%***	-0.53%**	-0.74%***	-0.54%	0.06%	2.06%**	1.52%**	485
[-5%, 5%)	-0.79%***	1.14%***	0.02%	-0.12%***	-0.20%***	-0.08%***	0.90%***	0.96%***	1.02%***	1.11%***	28513
[-6%,-5%)	-0.57%***	0.72%***	0.13%***	0.08%**	0.02%	0.02%	1.21%***	1.06%***	1.16%***	1.09%***	7857
[-7%,-6%)	-0.67%***	0.65%***	0.11%***	0.03%	0.02%	0.11%***	1.50%***	1.30%***	1.26%***	1.27%***	6848
[-8%,-7%)	-0.72%***	0.76%***	0.15%***	0.00%	0.04%	0.11%**	1.76%***	1.30%***	1.25%***	1.32%***	5401
[-9%,-8%)	-0.92%***	0.87%***	0.21%***	-0.01%	0.12%**	0.13%**	2.18%***	1.24%***	1.01%***	1.27%***	4403
(-10%,-9%)	-0.86%***	0.85%***	0.32%***	0.23%***	0.13%**	0.20%***	2.29%***	1.43%***	1.45%***	1.69%***	5238
Lower Hit	-2.92%***	-0.49%***	-0.19%***	0.02%	0.16%***	0.12%***	2.28%***	2.90%***	1.36%***	2.09%***	16653

3.6.4 Robustness checks

Up to this point we have followed Dennis and Strickland (*op cit.*), in defining extreme market movements as occurring on days when the absolute value of market return (as expressed in the relevant composite stock price index) exceeds three standard deviations above mean. We have repeated this analysis with the alternative definition of extreme market movements exceeding three standard deviations from the mean. Over our full sample, 2010-2017 this obviously results in fewer extreme market movement days (13 up and 24 down days in the Shenzhen stock market and 4 up and 25 down extreme market movement days in the Shenzhen stock market). Given the much reduced sample for the Shenzhen up days we omit analysis of these but can report that the remainder of the results are quantitatively and qualitatively very similar to the core results discussed above.

Table 3.5: Regression analysis of abnormal returns on regular stocks in Shanghai Stock Exchange

The table reports the results of estimating equations (3-5) and (3-6) to explain the abnormal returns or cumulative abnormal returns of regular stocks in the days following extreme market movement days that occurred in the Shanghai stock market over the period 2010 to 2017. Panel A reports the results for extreme up days, in which the key variable UPPER refer to regular stocks hitting 10% upper price limit and NETBUY refers to large net buy transactions of institutional investors on the extreme market up days. Panel B reports the regression results for abnormal returns on regular stocks following extreme market down days, where LOWER refers to regular stocks that hit the -10% price limit and NETSELL to the large net sell transactions of institutional investors on extreme market down days. Control variables in each regression include SIZE, TURNOVER, VARIANCE and BETA. All variables are as defined in section 3.3. Standard errors are clustered by firm and t-statistics are reported in parentheses. "***", "**" and "*" represent statistical significance at 1%, 5% and 10% levels respectively.

Panel A Abnormal returns in Shanghai stock market subsequent to extreme market up days									
	AR Day1	AR Day2	AR Day3	AR Day4	AR Day5	CAR [6,10]	CAR [11,20]	CAR [21,60]	CAR [61,120]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
UPPER	0.035***	0.011***	-0.008***	0.004***	0.010***	0.005	-0.031***	-0.006*	-0.008***
	(25.6)	(9.96)	(-7.37)	(3.43)	(11.0)	(1.30)	(-7.83)	(-1.85)	(-2.60)
NETBUY	0.056	-0.140***	0.017	0.088**	-0.030	0.145	-0.482***	-0.292*	-0.070
	(1.08)	(-3.27)	(0.47)	(2.11)	(-0.84)	(0.94)	(-2.63)	(-1.69)	(-0.60)
UPPER *	0.468***	0.497***	0.192**	-0.397***	-0.111*	0.008	1.252***	0.762***	0.256
NETBUY	(4.61)	(6.16)	(2.46)	(-4.99)	(-1.70)	(0.04)	(4.26)	(3.39)	(1.27)
[8%, 10%)	-0.010***	-0.009***	-0.003***	0.012***	0.001	-0.007*	-0.041***	-0.008**	-0.014***
	(-8.05)	(-8.38)	(-2.75)	(11.5)	(0.86)	(-1.72)	(-9.50)	(-2.22)	(-4.52)
[8%, 10%)*	0.661***	0.669***	0.110	-0.423***	-0.028	-0.842	1.389**	1.483***	0.893**
NETBUY	(3.83)	(4.80)	(0.92)	(-3.14)	(-0.25)	(-1.35)	(2.43)	(3.16)	(1.98)
[6%, 8%)	0.000	-0.004***	-0.001*	0.007***	-0.002***	-0.009***	-0.020***	-0.006***	-0.012***
	(-0.01)	(-5.97)	(-1.72)	(9.375)	(-3.36)	(-3.38)	(-7.26)	(-2.82)	(-5.64)
[6%, 8%)*	-0.035	0.408***	-0.027	-0.304***	-0.206**	-0.005	1.229***	0.176	0.694**
NETBUY	(-0.32)	(3.19)	(-0.19)	(-3.50)	(-2.49)	(-0.01)	(4.23)	(0.51)	(2.55)
[4%, 6%)	0.006***	-0.001***	0.001	0.003***	-0.001**	0.001	-0.008***	-0.008***	-0.002
	(10.5)	(-2.77)	(1.38)	(6.01)	(-2.55)	(0.54)	(-4.59)	(-5.29)	(-1.43)
[4%, 6%)*	-0.494***	0.555***	0.315***	0.188*	-0.026	0.779**	0.879**	0.549	-0.080
NETBUY	(-4.35)	(5.72)	(2.89)	(1.90)	(-0.23)	(2.02)	(1.97)	(1.52)	(-0.25)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.04***	0.031***	0.014***	-0.017***	0.012***	-0.002	-0.032**	0.079***	0.034***
	(11.5)	(9.74)	(4.61)	(-6.43)	(4.41)	(-0.18)	(-2.37)	(7.50)	(2.88)
No. Obs.	37409	37408	37408	37408	37408	37405	37394	37349	37240
Adjusted R^2	0.082	0.039	0.013	0.015	0.011	0.003	0.020	0.002	0.002
Panel B Abnormal returns in Shanghai stock market subsequent to extreme market down days									
LOWER	-0.027***	-0.006***	-0.005***	0.000	-0.007***	-0.04***	0.034***	-0.008***	0.006***
	(-34.3)	(-9.09)	(-8.43)	(0.24)	(-11.3)	(-14.9)	(14.5)	(-4.32)	(4.04)
NETSELL	0.167**	0.033	0.071	-0.025	-0.080	-0.154	-0.197	0.108	-0.010
	(2.54)	(0.62)	(1.33)	(-0.52)	(-1.61)	(-0.76)	(-1.05)	(0.75)	(-0.11)
LOWER*	-0.273	-0.128	-0.837***	-0.733***	0.127	-2.450***	-1.926***	0.626	0.024
NETSELL	(-1.58)	(-1.13)	(-6.38)	(-5.63)	(1.06)	(-5.54)	(-5.32)	(1.52)	(0.10)
(-10%,-8%]	-0.005***	0.002***	-0.003***	0.002***	0.005***	0.002	0.006**	-0.003	0.000
	(-6.29)	(3.27)	(-5.07)	(3.01)	(7.41)	(0.81)	(2.36)	(-1.60)	(0.08)
(-10%,-8%]*	-0.214	-0.433***	-0.664***	-0.672***	0.138	-1.864***	-0.541	-0.537	-0.373
NETSELL	(-0.99)	(-3.18)	(-4.21)	(-4.50)	(0.89)	(-3.30)	(-1.07)	(-1.17)	(-1.01)
(-8%,-6%]	-0.006***	0.001***	-0.002***	0.001***	0.003***	0.001	0.000	-0.003*	-0.003*
	(-7.96)	(2.89)	(-2.87)	(2.64)	(6.46)	(0.51)	(0.04)	(-1.69)	(-1.65)
(-8%,-6%]*	-0.568***	-0.257*	-0.166	-0.310**	-0.093	-0.728	1.090*	1.034*	0.097
NETSELL	(-2.77)	(-1.72)	(-1.04)	(-2.18)	(-0.59)	(-1.32)	(1.92)	(1.84)	(0.23)
(-6%,-4%]	-0.004***	0.002***	0.000	0.002***	0.002***	0.001	0.004**	-0.001	0.000
	(-7.29)	(5.28)	(0.40)	(3.90)	(4.01)	(0.72)	(1.97)	(-0.53)	(-0.37)
(-6%,-4%]*	-0.588**	-0.387**	-0.017	-0.205	-0.062	-0.096	-0.206	0.535	-0.050
NETSELL	(-2.33)	(-2.51)	(-0.10)	(-1.34)	(-0.44)	(-0.22)	(-0.39)	(1.47)	(-0.20)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes

Constant	-0.025***	-0.026***	-0.024***	-0.04***	-0.022***	-0.029**	0.067***	0.036***	0.068***
	(-5.30)	(-8.25)	(-8.13)	(-11.4)	(-5.78)	(-2.34)	(5.90)	(3.85)	(8.00)
No. Obs.	43629	43628	43627	43626	43625	43620	43604	43535	43395
Adjusted R^2	0.068	0.012	0.022	0.021	0.034	0.014	0.012	0.002	0.001

Table 3.6: Regression analysis of abnormal returns on regular stocks in Shenzhen Stock Exchange

The table reports the results of estimating equations (3-5) and (3-6) to explain the abnormal returns or cumulative abnormal returns of regular stocks in the days following extreme market movement days that occurred in the Shenzhen stock market over the period 2010 to 2017. Panel A reports the results for extreme up days, in which the key variable UPPER refer to regular stocks hitting 10% upper price limit and NETBUY refers to large net buy transactions of institutional investors on the extreme market up days. Panel B reports the regression results for abnormal returns on regular stocks following extreme market down days, where LOWER refers to regular stocks that hit the -10% price limit and NETSELL to the large net sell transactions of institutional investors on extreme market down days. Controls included in each regression include SIZE, TURNOVER, VARIANCE and BETA, as defined in section 3.3. Standard errors are clustered by firm, t-statistics are reported in parentheses. "***", "**" and "*" represent statistical significance at 1%, 5% and 10% levels respectively.

Panel A Abnormal returns in Shenzhen stock market subsequent to extreme market up days

	AR Day1 (1)	AR Day2 (2)	AR Day3 (3)	AR Day4 (4)	AR Day5 (5)	CAR [6,10] (6)	CAR [11,20] (7)	CAR [21,60] (8)	CAR [61,120] (9)
UPPER	0.026***	0.008***	0.000	0.001**	0.006***	0.005*	-0.001	0.000	0.002
	(22.2)	(10.7)	(-0.61)	(1.96)	(8.61)	(1.80)	(-0.45)	(-0.10)	(0.77)
NETBUY	-0.969***	-0.167**	-0.342***	-0.413***	-0.054	1.325***	-0.388*	0.154	0.122
	(-6.84)	(-2.43)	(-4.61)	(-5.83)	(-0.82)	(3.27)	(-1.85)	(0.68)	(0.480)
UPPER*	1.413***	0.182**	0.451***	0.308***	-0.038	-1.56***	-0.129	-0.020	-0.254
NETBUY	(8.547)	(2.149)	(5.192)	(3.662)	(-0.50)	(-3.53)	(-0.45)	(-0.07)	(-0.873)
[8%, 10%)	-0.011***	-0.001	0.000	0.007***	0.001	0.007**	-0.005	-0.001	-0.007***
	(-8.395)	(-1.073)	(-0.62)	(10.531)	(1.26)	(2.19)	(-1.60)	(-0.28)	(-2.903)
[8%, 10%)*	1.524***	0.210	0.195	-0.043	-0.107	-1.772***	0.425	0.121	0.249
NETBUY	(5.092)	(1.635)	(1.317)	(-0.377)	(-0.98)	(-3.46)	(1.30)	(0.36)	(0.66)
[6%, 8%)	-0.005***	0.001**	0.002***	0.004***	0.000	0.011***	0.000	0.004**	-0.008***
	(-5.068)	(1.974)	(3.499)	(9.239)	(0.49)	(4.90)	(0.06)	(2.11)	(-3.846)
[6%, 8%)*	1.39***	0.101	0.469***	0.064	0.057	-1.478***	-0.168	-1.293***	0.172
NETBUY	(5.323)	(0.949)	(4.226)	(0.586)	(0.58)	(-2.56)	(-0.45)	(-2.86)	(0.42)
[4%, 6%)	0.001*	0.001***	0.002***	0.002***	0.001**	0.004**	0.000	-0.001	-0.003**
	(1.797)	(2.56)	(6.325)	(5.63)	(2.08)	(2.35)	(-0.08)	(-0.65)	(-2.14)
[4%, 6%)*	1.33***	0.214	0.174*	0.206	0.219*	-0.131	-0.288	0.396	1.239
NETBUY	(6.197)	(1.496)	(1.666)	(1.476)	(1.84)	(-0.21)	(-0.65)	(1.04)	(1.42)
Control	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.066***	0.029***	0.01***	0.007**	0.009***	0.06***	0.017	0.029**	0.044***
	(15.592)	(10.523)	(3.764)	(2.455)	(3.501)	(4.45)	(1.362)	(2.484)	(3.805)
No Obs.	47534	47533	47533	47532	47530	47523	47508	47363	47000
R^2	0.047	0.017	0.004	0.007	0.006	0.003	0.001	0.001	0.001

Panel B Regular stocks from Shenzhen down extreme days

	AR Day1 (1)	AR Day2 (2)	AR Day3 (3)	AR Day4 (4)	AR Day5 (5)	CAR (6)	CAR (7)	CAR (8)	CAR (9)
LOWER	-0.043***	-0.001***	0.002***	0.004***	0.002***	0.014***	0.020***	0.003***	0.01***
	(-64.9)	(-2.93)	(4.97)	(13.3)	(6.51)	(7.85)	(13.5)	(2.61)	(7.62)
NETSELL	0.033	0.056*	-0.014	-0.03	0.091***	-0.043	-0.048	-0.172*	-0.214
	(0.61)	(1.79)	(-0.38)	(-0.876)	(2.93)	(-0.37)	(-0.51)	(-1.73)	(-1.42)
LOWER*	1.124***	0.189***	0.158**	-0.168**	-0.06	-0.012	0.020	0.388*	-0.017
NETSELL	(9.37)	(2.87)	(2.04)	(-2.40)	(-0.87)	(-0.04)	(0.07)	(1.69)	(-0.08)
(-10%,-8%]	-0.009***	0.004***	0.003***	0.004***	0.003***	0.014***	0.005***	0.003*	0.004***
	(-12.3)	(9.84)	(7.70)	(10.2)	(7.00)	(8.25)	(3.50)	(1.74)	(2.81)
(-10%,-8%]*	0.347**	-0.249**	0.027	0.081	0.002	-0.336	-0.345	0.162	0.006
NETSELL	(1.98)	(-2.34)	(0.27)	(0.94)	(0.03)	(-0.98)	(-1.05)	(0.52)	(0.02)
(-8%,-6%]	-0.007***	0.002***	0.002***	0.003***	0.002***	0.009***	0.004***	0.002*	0.001

	(-10.7)	(5.55)	(5.34)	(8.29)	(7.01)	(6.29)	(2.78)	(1.66)	(0.87)
(-8%,-6%]*	-0.194	0.078	0.033	0.032	-0.109	-0.886***	0.035	0.617**	0.34
NETSELL	(-1.05)	(0.91)	(0.33)	(0.46)	(-1.36)	(-2.87)	(0.11)	(2.05)	(0.94)
(-6%,-4%]	-0.005***	0.002***	0.002***	0.002***	0.001***	0.004***	0.002	0.001	-0.001
	(-8.92)	(6.86)	(7.77)	(6.95)	(3.65)	(3.70)	(1.47)	(0.71)	(-1.41)
(-6%,-4%]*	-0.253*	-0.231**	0.008	0.116	0.028	-0.295	-0.04	0.387	0.000
NETSELL	(-1.88)	(-2.44)	(0.08)	(1.52)	(0.34)	(-0.93)	(-0.13)	(1.51)	(0.00)
Control	yes	yes	yes	yes	yes	yes	yes	yes	yes
constant	-0.035***	-0.008***	-0.011***	-0.003	0.003	-0.033***	0.054***	0.030***	0.067***
	(-8.73)	(-3.59)	(-4.87)	(-1.62)	(1.49)	(-3.12)	(5.93)	(3.49)	(8.45)
No. Obs.	75678	75672	75663	75661	75653	75634	75589	75342	73219
Adjusted R^2	0.074	0.005	0.006	0.006	0.002	0.003	0.004	0.000	0.002

3.7 Conclusions

Using daily stock returns of all stocks listed in the Shanghai and Shenzhen Stock Exchanges over the period 2010 to 2017 we have identified the highly volatile extreme market movement days in each market and have focused on the impacts of institutional trading on these days. We contribute to the existing literature by two ways in constructing a more appropriate proxy for daily institutional investors' trading and accounting the effect of price limit in the study of extreme days in China's stock market. We hope the findings contained in this chapter will be of interest to the financial practitioners in understanding the sources and patterns of market swings and also to policymakers to evaluate the effectiveness of imposed price limit rule played on and after extreme days.

Our descriptive statistics suggest that on average, institutional investors engage in net buy (sell) behaviour on extreme up (down) days. Regression results provide strong evidence that the large net trades in firm-level stocks attributable to institutional investors have a significant destabilizing effect on firm-level abnormal returns on extreme market up and down days, in both Chinese stock markets. The fact that our results contrasts with those of Tian *et al.* (*op cit.*), suggests that the quarterly institutional ownership data used in prior extreme day studies does not provide sufficient variation to capture daily institutional trading behaviour.

We are also able to show that abnormal turnover is also exacerbated by institution trading activity on extreme market up days although it seems that abnormal turnover falls on extreme market down days. We suggest that the interaction of institutional trading and the propensity of stocks hitting binding price limits on extreme down days may explain the latter result. This motivates us to incorporate consideration of the daily price limits imposed by the Chinese stock market regulator into our analysis, again this is a novel contribution to the literature on extreme market movement days which allows for the possibility that institutional trading activity has distinctive impacts on the subsequent price dynamics of individual stocks that hit the upper (lower) binding price limits during extreme market up (down) days. Specifically we focus on whether or not high value institutional trades in shares that hit price limits on extreme market movement days can help to predict abnormal returns in subsequent days. In doing so we draw on the work of Chen *et al.* (2019), though note that while they found evidence of destabilizing behaviour following stocks hitting upper price limits, they did not focus purely on extreme market up days and nor did they extend their analysis to include days in which stocks hit lower price limits.

Our analysis of post-extreme day abnormal returns provides strong evidence that high value institutional trades in price limit hitting stocks on extreme market movement days does indeed have significant predictive power for these abnormal returns in these stocks in the days subsequent to extreme market movements. More specifically we find that the price limit results in delayed price discovery particularly when it binds, the delayed effect is much stronger than that in all trading-days investigation (Chen *et al.*, 2019). So, high value institutional trades in price-limit-hitting stocks on extreme market movement days not only exacerbate the volatile market on these extreme market movement days, they continue to predict abnormal returns, in the same direction, for several subsequent days. We note that this does not necessarily mean that institutional trading is to blame for the subsequent movements, rather it may be the trades of large numbers of individual (retail) investors who are less well informed yet have their attention drawn to the affected stocks as a result of large net institutional trades and the binding price limits.

The fact that these clear patterns of destabilizing impacts are absent in the subsequent firm-level abnormal returns for stocks that recorded within limit price movements on extreme market movement days adds support to our conclusion that distinctive and significant subsequent price dynamics look to be concentrated in those stocks that are the focus of high value institutional trades and hit the stock market regulator imposed price limits on the extreme market movement days.

Finally, as the rule of price limits imposed was to cool down the irrational trading behaviour, our results of destabilizing role played by price limit also contain implications to policymakers in the process towards financial liberalization in China’s stock market.

Chapter 4

4. The Idiosyncratic Risk in Chinese Stock Market: From a Volatility Decomposition Perspective

4.1 Introduction

The Chinese stock market, the largest emerging stock market in the world, is demonstrably more volatile than the other international stock markets (e.g. Wang et al., 2011; Li and Giles, 2015; Rizvi et al., 2018)[11]. The recent 2015-2016 stock market crash is attracting renewed attention of researchers on the investigation of the volatility of Chinese stock markets (Tian et al., 2018; Chap. 3, page 39). This chapter seeks to uncover the sources and patterns of high volatility in Chinese stock market by using a volatility decomposition approach. As Chinese stock market has been growing rapidly in recent years, understanding the volatility dynamics in Chinese stock market is an undoubtedly important issue for global investors who seek for portfolio diversification in international of industrial levels, and for financial regulators to identify the pattern of risks in Chinese stock market.

In order to identify and study the source of the volatility in the U.S. stock market, Campbell, Lettau, Malkiel and Xu (hereafter CLMX, 2001) propose a volatility decomposition approach which disaggregates the volatility of common stocks into the market, industry and idiosyncratic components. The volatility decomposition approach of CLMX enables a clean disaggregation of total return volatility into market, industry and idiosyncratic components. Using this volatility decomposition approach, a number of studies extend the research in U.S. stock market to examine the relation between the decomposed volatility and trading activity of retail investor (Brandt et al., 2010) or the volatility patterns across individual industries (Wang, 2010).

Although volatility decomposition in U.S. stock markets has been well established, much less attention has been drawn to the Chinese stock market. Following CLMXs' volatility decomposition approach, we address the following specific questions as i) What is the key source of high volatility in Chinese stock market? ii) What are the time-series behaviours of

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We are grateful to Timothy J. Vogelsang for his helpful comments on the trend function hypothesis testing. This chapter also benefits from the comments on presentation at 22nd Dynamic Econometrics conference held in Nuffield College Oxford in September 9-10, 2019.

[11] See next section for detailed discussion.

the volatilities? iii) Who is responsible for the time-series behaviour of idiosyncratic volatility, institutional or individual investors? iv) What is the pattern of volatility across industries?

In our study, by utilizing the daily return data of all listed firms in Chinese stock markets (i.e. Shanghai and Shenzhen Stock Exchanges) over 1998 to 2018, we decompose the volatility of common stocks into market, industry and idiosyncratic volatility. We demonstrate that China's market level volatility is the largest component of volatility, contrasting with US decompositions that attribute the largest and growing component of volatility to the firm level. This finding can be explained by the evidence of higher stock price synchronicity or lower firm-specific return variation in Chinese stock market (e.g. Gul et al., 2010). Also, while market volatility tends to drive industry and firm volatility in the US stock market, we demonstrate that firm level idiosyncratic volatility tends to drive both industry and market volatility in China.

In order to identify the time series behaviours of market, industry and idiosyncratic volatilities, we first use the trend test developed by Bunzel and Vogelsang (2005) and demonstrate that there is no long-term trend for in any of the volatility series. Given that the results of the trend test can be driven by the selection of starting and ending time points (e.g. Bakaert et al., 2012), we fit a Markov regime-switching model with a first-order autocorrelation structure (AR (1)) for each of the three volatility series[12]. We find that all the three volatilities are characterised by an autoregressive with regime shifts, and the shifts of market and industry volatilities to a high variance regime are mostly related to crisis periods in financial markets. Idiosyncratic volatility, however, exhibits less stable features compared to market industry volatilities, and shifts to and from high variance regimes more frequently.

We proceed to investigate the question of whether institutional or retail investors are responsible for the time-series behaviour of idiosyncratic volatility. Despite Nartea et al. (2013) conjecture that the idiosyncratic volatility is associated with retail investors due to the dominant retail trading in Chinese stock market, the more recent studies by Chen et al. (2019) and Darby et al. (2019) demonstrate that destabilizing behaviour of large or institutional investors on firm abnormal returns in the Chinese stock market. Following Darby et al. (2019), we use the cash flow data from the largest trading group as the proxy for institutional trading and find that the idiosyncratic volatility is significantly associated with high stock prices and the trading activities of institutional investors. Our results contrast the findings of Brandt et al. (2010) for the U.S. stock market. We show that our results are robust to using other measures

[12] See among others, Bakaert et al., 2012; Nartea et al., 2013; Garcia et al., 2014.

of idiosyncratic volatility such as CAPM and the risk factors from the Fama-French three factors model.

Finally, we provide more evidence of idiosyncratic volatility from an industry-level investigation which allows us to identify the variation and dynamic patterns across industries. We first present the evidence of no long-term trend for each of the largest 15 industries in Chinese stock markets. We infer that the absence of a trend in volatility is nor therefore due to the trade-off effect of mixed upward and downward trends across industries. We then find the firm-specific volatility is particularly high in the manufacturing industry, the largest industry represented in the Chinese stock market, accounting for the average weight of 0.393 in total market value. Furthermore, the multivariate Granger causality tests suggest firm-specific volatility in the manufacturing industry is also a lead indicator for idiosyncratic volatility in other industries.

This Chapter contributes to the literature in the following three respects. First, to the best of our knowledge, this is the first Chapter decomposing the volatility of common stocks into market, industry and firm level components identifying the source of high aggregate volatility in the Chinese stock market. Second, we contribute to a number of recent studies on idiosyncratic volatility in Chinese stock market[13]. We show that idiosyncratic volatility in the Chinese stock market is associated with high stock prices and driven by institutional investors. This contrasts the findings in U.S. stock market (Brandt et al., 2010) and the conjecture of Nartea et al. (2013). Third, we take the first attempt to investigate volatility patterns across individual industries represented in the Chinese stock market. As industry allocation is an increasingly important consideration for active institutional investors (e.g. Cavaglia et al., 2000, Carrieri et al., 2004), our results also contain the implications for investors who consider for home-biased equity allocation policies.

The rest of the Chapter is organized as follows. Section 4.2 provides the literature review. Section 4.3 introduces the data and the methodology of volatility decomposition. The time series behaviours of three decomposed volatility components have been reported in Section 4.4. Section 4.5 conducts cross-sectional regressions testing the key determinants of idiosyncratic volatility in Chinese stock markets and is followed by investigations into the sources and patterns of volatility within individual industries in Section 4.6. Section 4.7 concludes. The results of the dynamic pattern of industry-specific volatility in individual

[13] See Wan, 2018, Gu et al., 2018, Xie et al., 2019 and Gu et al., 2019 among others.

industries can be accessed in Appendix D, while the robustness checks related to the retail trading are presented in Appendix E.

4.2 Literature Review

A number of recent studies point towards the fact that the volatility in Chinese stock market is higher than that of the other international stock markets. In comparison with the standard deviations across different MSCI indices, Wang et al. (2011) show the standard deviation of MSCI China index is higher than that of the world, U.S., Europe, Japan, and Pacific indices from 2000 to 2009. Similarly, Li and Giles (2015) report that the standard deviation of the return of Shanghai Composite Index is higher than the other five Asian emerging markets over periods from 1993 to 2012. Using MSCI indices of 21 emerging stock markets, Rizvi, et al. (2018) also show the conditional volatility of China Index return estimated by GARCH model is higher than that of others from 2001 to 2014. Although the evidence of high volatility in China’s stock market is well examined, the research on the investigation on the components and sources of the high volatility remains limited.

To investigate the source of volatility in U.S. stock market, a series of research has examined the patterns of the components of aggregated volatility using the volatility decomposed approach proposed by CLMX (2001). Using daily stock excess returns data, CLMX propose a volatility decomposition approach that disaggregates the volatility of common stocks into the market, industry and idiosyncratic components. They find idiosyncratic volatility is greater than the market and industry volatilities, and market volatility tends to lead the other volatility series. They also document a notable increase in firm-level volatility relative to market volatility from 1962 to 1997. However, Brandt et al. (2010) show that the positive trend of idiosyncratic volatility in U.S. stock market is partly of an episodic phenomenon when extending the investigation period to 2008. In addition, they also show the episodic phenomenon of idiosyncratic volatility is associated with the trading activities of retail investors by using cross-sectional regressions. Another related study by Wang (2010) further highlights the importance of CLMXs’ contribution to the analysis of stock return volatility at the industry level. By adopting multivariate Granger causality tests, they find the industries of business supplies and finance are the top two lead indicators of industry-specific volatilities over the period 1963 to 2008 in the U.S. stock market. Although the sources and patterns of volatility have been well examined by using CLMX volatility decomposition approach, to our best of knowledge, no prior studies have adopted this approach into China’s stock market. Therefore, we apply the volatility decomposition framework into China’s stock market to fill in the following these research gaps to investigate the decomposed volatility patterns and the relation between idiosyncratic volatility and the trading activity of investors.

The pattern and driver of idiosyncratic volatility are of the particular interest among all three decomposed volatility series to investors as the increased idiosyncratic volatility benefits the portfolio diversification (CLMX, 2001, Brandt et al., 2010). The existing literature provides mixed evidence on whether institutional investors or retail investors drive to the idiosyncratic volatility. Xu and Malkiel (2003) investigate the mechanisms behind the increase in idiosyncratic volatility during the 1980s and 1990s in U.S. stock market and find that idiosyncratic volatility is associated with institutional ownership and high growth. On the contrary, Brandt et al., (2010) find the idiosyncratic volatility in U.S. stock market is associated with low-priced stocks and the trading activity of retail investors by using small-sized trades are used as a proxy for retail trades. Che (2018) investigate how different types of investors affect stock return volatility in from 1992 to 2007 in Norwegian stock market, and provide evidence that individual investors reduce stock return volatility and idiosyncratic volatility because they act as contrarian traders in the market. A closer study by Nartea et al. (2013) investigates the time-series behaviour of idiosyncratic volatility in Chinese stock market and finds no evidence of a long-term trend from 1994 to 2011. The aggregate idiosyncratic volatility is described as by autoregressive process with regimes shift associated with structural market reforms. In addition, due to the retail dominance in stock trading in Chinese stock market, they also present supporting evidence that the episodic idiosyncratic volatility is associated with retailing trading. Although Nartea et al. (2013) conjecture that idiosyncratic volatility in China's stock market is associated with trading activities by retail investors, as far as we know, no previous research has tested this hypothesis, which still remains a research gap.

In summary, this chapter aims to fill in the research gaps in three perspectives by using CLMX volatility decomposition approach, which are i) to investigate the patterns of decomposed volatility; ii) to identify whether idiosyncratic volatility is associated with the trading activity of retail investors; and iii) to examine the dynamic patterns of volatility across individual industries.

4.3 Volatility decomposition

4.3.1 Data

We obtain the daily market return data and stock return data of all listed firms in Shanghai and Shenzhen stock markets for the period of Jan 1998 through Dec 2018 from China Stock

Market & Accounting Research Database (CSMAR). The cash flow, risk free return, and Fama-French (1993) factors data are derived from RESSET (www.resset.cn) database. The quarterly institutional ownership data is sourced from WIND database and the other firm-specific accounting data is obtained from CSMAR database. Finally, we use "Guidelines for the Industry Classification of Listed Companies" (2012 Revision) issued by China Securities Regulatory Commission (CSRC) for the industry classification of listed firms. The numbers of firms included in samples are 804 in the year of 1998, 1664 in year 2009, and finally increase to 3568 at the end of study periods of 2018.

4.3.2 Methodology

Following Campbell, Lettau, Malkiel, and Xu (hereafter, CLMX) (2001) and Brandt et al. (2010), we employ the approach of the beta-free volatility decomposition to study the volatility of common stocks at the market, industry and firm levels. Let R_{mt} and R_{it} denote the excess returns of market and industry i in period t respectively. The excess return of firm j that belongs to industry i in period t is denoted as R_{jit}. Therefore, the industry excess return R_{it} is given by $R_{it} = \sum_{j \in i} w_{jit} R_{jit}$ where w_{jit} is the weight of firm j in industry i over period t. Consequently, the excess market return $R_{mt} = \sum_{i} w_{it} R_{it}$ where w_{it} is the weight of industry i over period t.

We start with simplified industry return decomposition under the limitation of unit beta as follows:

$$R_{it} = R_{mt} + \varepsilon_{it}. \tag{4-1}$$

Computing the variance of the industry return yields:

$$Var\ (R_{it}) = Var\ (R_{mt}) + Var\ (\varepsilon_{it}) + 2Cov\ (R_{mt}, \varepsilon_{it}). \tag{4-2}$$

In order to overcome the drawback in equation (4-2) that R_{mt} and ε_{it} are not orthogonal, we then write down a decomposition based on the CAPM model:

$$R_{it} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it}. \tag{4-3}$$

Comparing equations (4-1) and (4-3), we have

$$\varepsilon_{it} = \tilde{\varepsilon}_{it} + (\beta_{im} - 1)Var\ (R_{mt}). \tag{4-4}$$

Putting equation (4-4) in equation (4-2), we then have

$$Var\ (R_{it}) = Var\ (R_{mt}) + Var\ (\varepsilon_{it}) + 2(\beta_{im} - 1)Var\ (R_{mt}). \tag{4-5}$$

Given the aggregate beta satisfies $\sum_i w_{it}\,\beta_{im} = 1$, the weighted average of variances across industries is free of the individual covariance as:

$$\sum_i w_{it}\,Var\,(R_{it}) = Var\,(R_{mt}) + \sum_i w_{it}\,Var\,(\varepsilon_{it}). \tag{4-6}$$

We proceed to decompose the individual firm returns in the same unit beta pattern:

$$R_{jit} = R_{it} + \varphi_{jit}. \tag{4-7}$$

The variance of firm return is represented as:

$$Var\,(R_{jit}) = Var\,(R_{it}) + Var\,(\varphi_{jit}) + 2Cov\,(R_{it}, \varphi_{jit}). \tag{4-8}$$

Likewise, in order to cancel the covariance term, we write down the CAPM model for a specific firm:

$$R_{jit} = \beta_{ji}R_{jt} + \tilde{\varphi}_{jit}. \tag{4-9}$$

Comparing equations (4-7) and (4-9), we have

$$\varphi_{jit} = \tilde{\varphi}_{jit} + (\beta_{ji} - 1)Var\,(R_{it}). \tag{4-10}$$

Putting equation (4-10) in equation (4-8), we then have

$$Var\,(R_{jit}) = Var\,(R_{it}) + Var\,(\varphi_{jit}) + 2(\beta_{ji} - 1)Var\,(R_{it}). \tag{4-11}$$

Given the aggregate beta satisfies $\sum_{j\epsilon i} w_{jit}\,\beta_{ji} = 1$, the weighted average of variances across firms is free of the individual covariance as:

$$\sum_{j\epsilon i} w_{jit}\,Var\,(R_{it}) = Var\,(R_{it}) + \sigma^2_{\varphi it}, \tag{4-12}$$

where $\sigma^2_{\varphi it} \equiv \sum_{j\epsilon i} w_{jit}\,Var\left(\varphi_{jit}\right)$ is the weighted average of idiosyncratic volatility in industry i. We further aggregate equation (4-12) by computing the weighted average across industries as follows:

$$\begin{aligned}\sum_i w_{it} \sum_{j\epsilon i} w_{jit}\,Var\left(R_{jit}\right) &= \sum_i w_{it}\,R_{it} + \sum_i w_{it} \sum_{j\epsilon i} w_{jit}\,Var\left(\varphi_{jit}\right)\\ &= Var\,(R_{mt}) + \sum_i w_{it}\,Var\,(\varepsilon_{it}) + \sum_i w_{it}\sigma^2_{\varphi it}\\ &= \sigma^2_{mt} + \sigma^2_{\varepsilon t} + \sigma^2_{\varphi t},\end{aligned} \tag{4-13}$$

where σ^2_{mt} is the market-level volatility; $\sigma^2_{\varepsilon t}$ is the weighted average of industry-level volatility across industries and $\sigma^2_{\varphi t}$ is the weighted average of firm-level volatility across all firms.

4.3.3 Estimation

Following the volatility decomposition framework of CLMX, we use daily market and stock excess returns to construct the monthly aggregate market volatility (MKT), industry volatility (IND) and idiosyncratic volatility (FIRM) respectively. In the CLMX volatility decomposition methodology, both the market returns and industry returns are constructed from aggregations of firm level returns with weights that reflect relative market capitalisation. The sample volatility of market return in month t, represented as MKT_t, is computed as:

$$MKT_t = \sum_{s\epsilon t}(R_{ms} - \mu_m)^2. \tag{4-14}$$

where μ_m is defined as the mean of market return R_{ms} in month t; s denotes the days in month t at which the returns are measured. The daily market return is measured as the market capitalization weighted return from all listed firms in Chinese stock market.

The volatility of industry i in month t is measured as the sum of the squares of industry-specific residuals in equation (4-1), and then the average industry capitalization weighted volatility is expressed as:

$$IND_t = \sum_i w_{it} \sum_{s\epsilon t} \epsilon_{is}^2. \tag{4-15}$$

where ϵ_{is}^2 is industry-specific volatility for industry i in month t; w_{it} is the weight for industry i in month t.

The estimation of average idiosyncratic volatility is conducted in a similar way. We first sum the squares of the firm-specific residuals in equation (4-7) in month t for each firm, and then compute the weighted average idiosyncratic volatility in each industry. Finally, we average over idiosyncratic volatility in all industries to obtain the average idiosyncratic volatility FIRM_t in month t as:

$$FIRM_t = \sum_i w_{it} \sum_{j\epsilon i} w_{jit} \sum_{s\epsilon t} \varphi_{jis}^2. \tag{4-16}$$

where φ_{jis}^2 is firm-specific volatility for firm j in industry i in month t; w_{jit} is the weight of firm j in industry i in month t; w_{it} is the weight for industry i in month t.

Figures 4.1, 4.2 and 4.3 present the monthly time series of volatility components (MKT, IND and FIRM), using daily firm-level stock return data from 1998 to 2018. The top panels show the raw monthly time series and the bottom panels show the moving average process with a lag of 12.

Market volatility shows its well-known patterns as various papers reported regarding index return volatility in Chinese stock markets. In comparison with Panel A and Panel B in Figure 4.1, market volatility is relatively stable and has a slow-moving component with high-frequency noise. A notable evidence of market volatility is that it is particularly high around 2008 and 2015, which reveals the fact that the stock market crashes in the year 2007-2008 and 2015-2016 led to an enormous increase in market volatility. Figure 4.2 plots the average industry volatility from 1998 to 2018, in which, on average, is lower than market volatility. Similar to market volatility, industry volatility is relatively stable compared to idiosyncratic volatility and particularly high around 2008 and 2015.

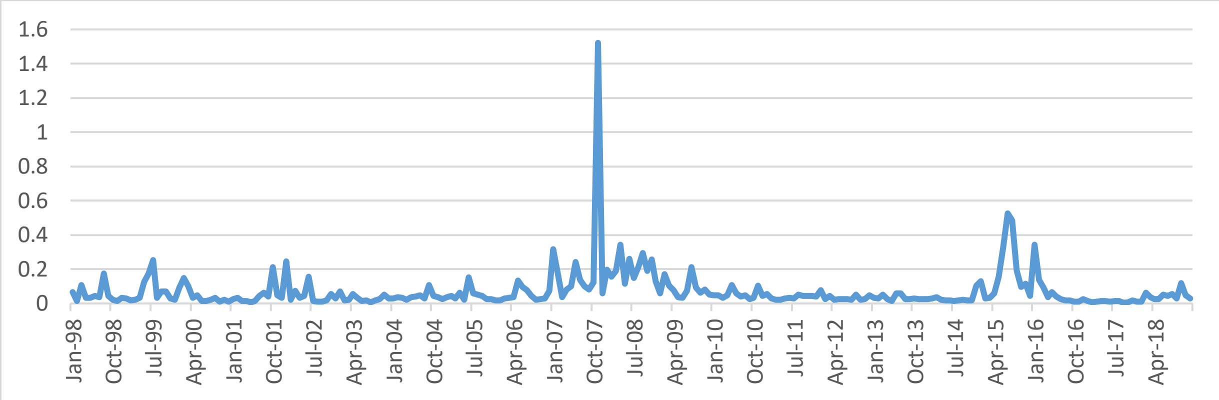
Figure 4.3 presents the idiosyncratic volatility FIRM from 1998 to 2018. Looking at both Panel A and Panel B for idiosyncratic volatility, the time series of FIRM shows its more volatile pattern compared to MKT and IND. Apart from the two market crash periods of year 2007-2008 and 2015-2016 that caused the enormous spikes in idiosyncratic volatility, idiosyncratic volatility is also particularly high around year 2005 and year 2013. In addition, the spikes in FIRM show its higher increase in the recent market crash of year 2015-2016 rather than that of 2007-2008, indicating that idiosyncratic volatility plays an important role in the weight of aggregate volatility for the firm on average.

In comparison with the three volatility components plots together, it is clear that both MKT and IND are relatively stable unless large spikes occurred during market crash periods. The idiosyncratic volatility FIRM, however, exhibits a more volatile feature with a larger amount of high-frequency noise and more spikes apart from the market crash period.

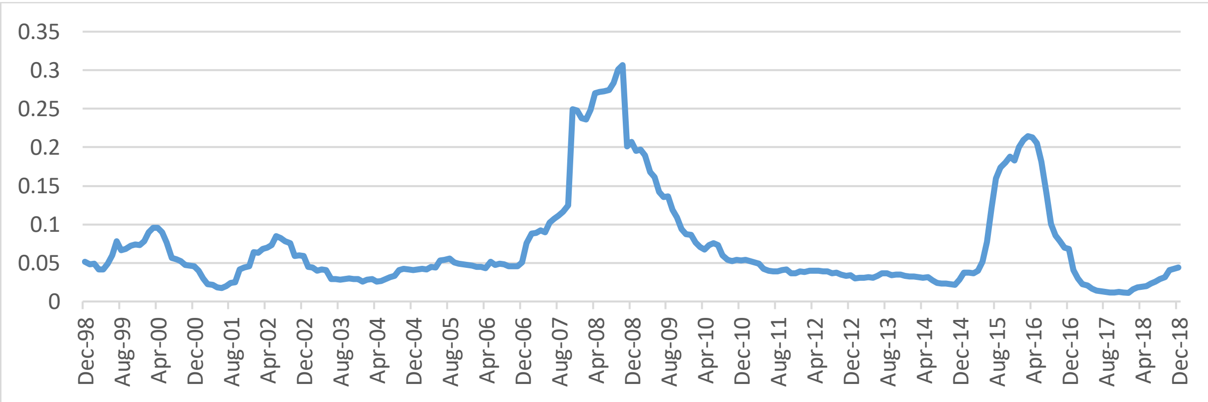
Figure 4.1: **Annualized market volatility MKT.**

The upper chart shows the annualized variance within each month of daily market returns over 1998 to 2018. The lower chart shows a backwards 12-month moving average of MKT.

Panel A. Market volatility



Panel B. Market volatility, MA (12)

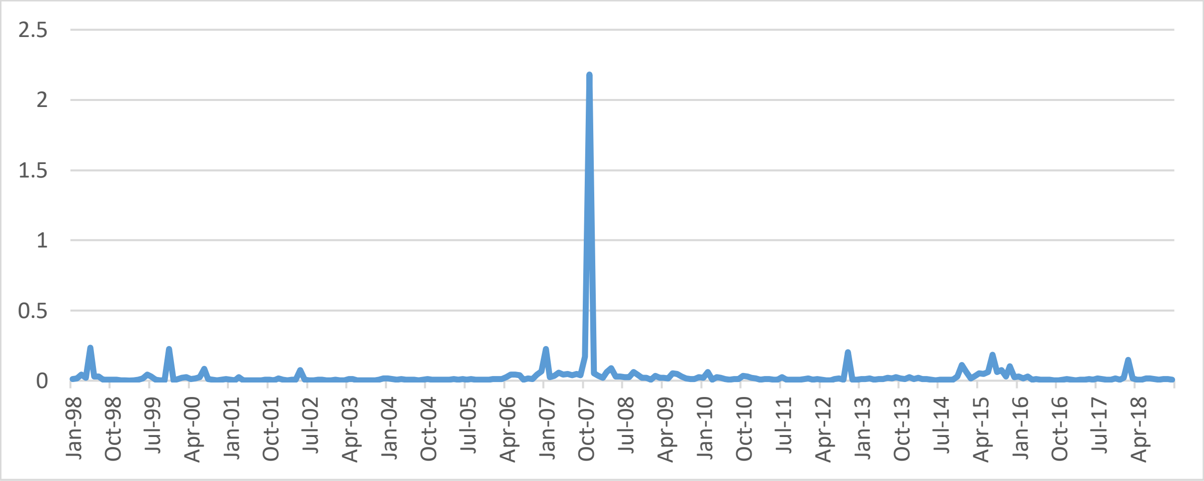


In order to identify the importance of each three volatility component in each month over the sample period, we further plot the weights of each volatility component in three together with backwards 12-month moving average processes based on the corresponding weights, as shown in Figure 4.4. For example, the weight applied to FIRM is calculated by FIRM divided by the sum of (MARKET+INDUSTRY+FIRM) by every month in figure 4.4. The same numerator is used in the construction of weights for INDUSTRY and MARKET. Consistent with the findings in Figure 4.1-4.3, the weight of IND is lower than MKT and FIRM in most of the observation periods. In comparison between market and idiosyncratic volatility, there is no consistent finding on whether MKT or FIRM is highest in most of the periods. Nevertheless, MKT tends to be higher than FIRM particularly in market crash periods, indicating the higher increased spikes in MKT than in FIRM in the market crash period. A plausible explanation is that financial markets' volatility increases substantially and move together during crisis[14], leading to the less amount of increased spikes of FIRM than that of MKT. Idiosyncratic volatility, however, is higher than market volatility in mainly three periods which are around 2006, 2014, and 2017.

Figure 4.2: **Annualized industry-level volatility IND.**

The upper chart shows the annualized variance within each month of daily industry returns relative to market over 1998 to 2018. The lower chart shows a backwards 12-month moving average of IND.

Panel A. Industry volatility



Panel B. Industry volatility, MA (12)

[14] See among others, Braun et al., 1995, Cappiello et al., 2003, Kotkatvuori-Ornberg et al., 2013.

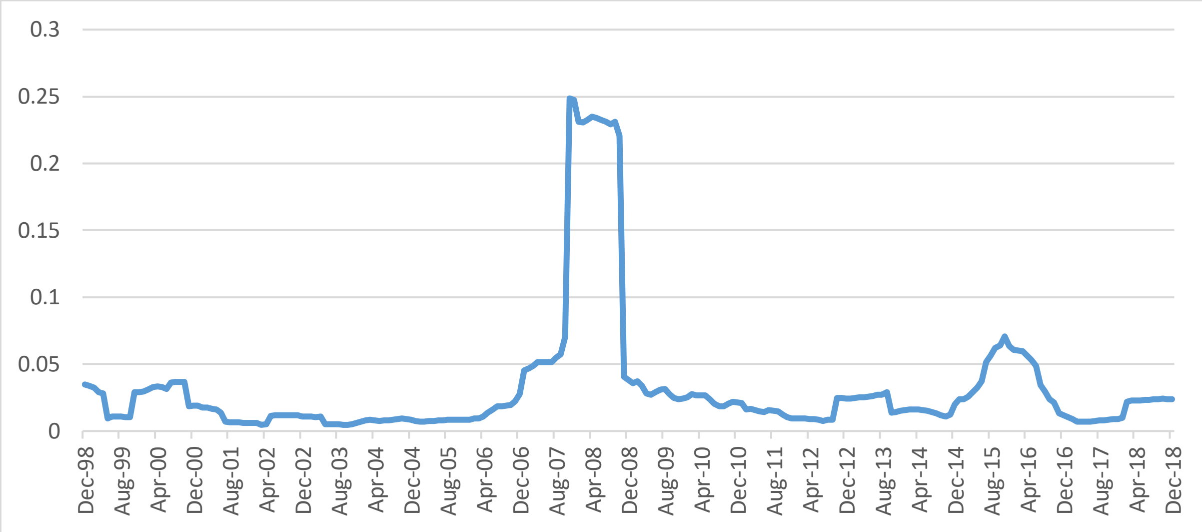
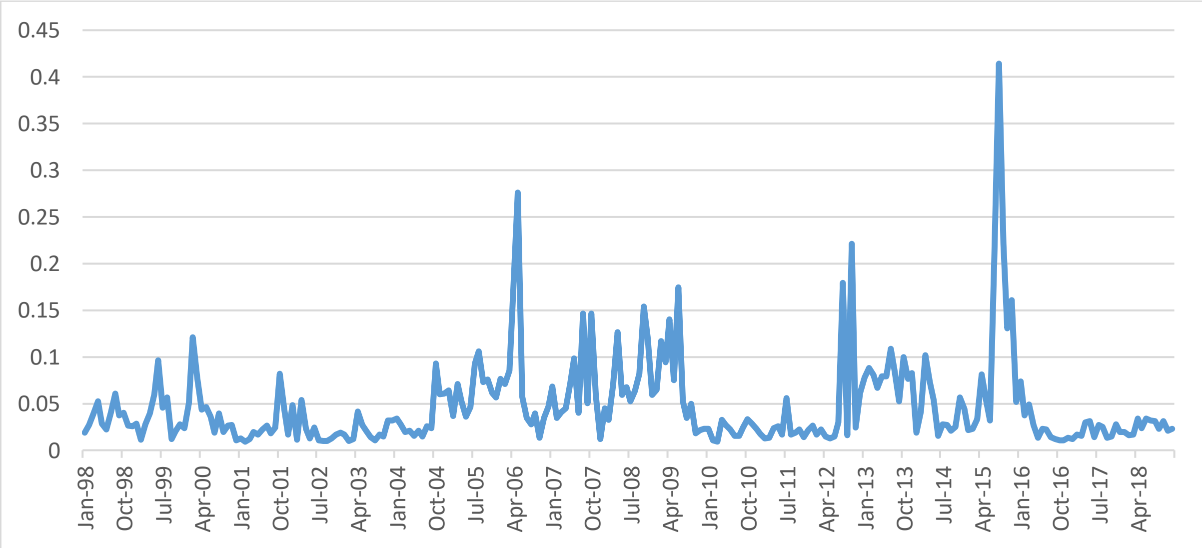


Figure 4.3: **Annualized firm-level volatility FIRM.**

The upper chart shows the annualized variance within each month of daily firm returns relative to the firm's industry over 1998 to 2018. The lower chart shows a backwards 12-month moving average of FIRM.

Panel A. Idiosyncratic volatility



Panel B. Idiosyncratic volatility, MA (12)

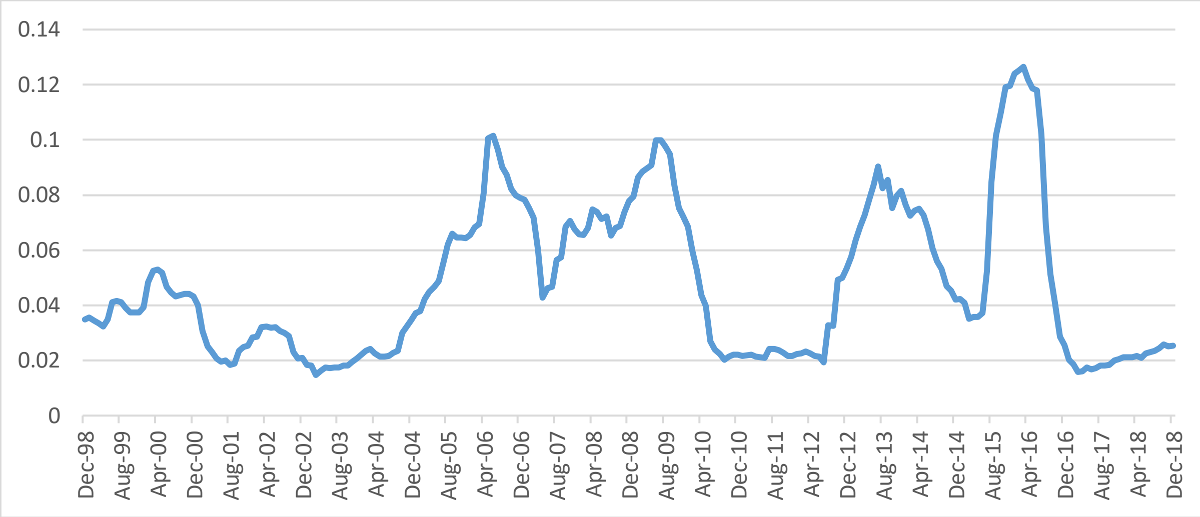
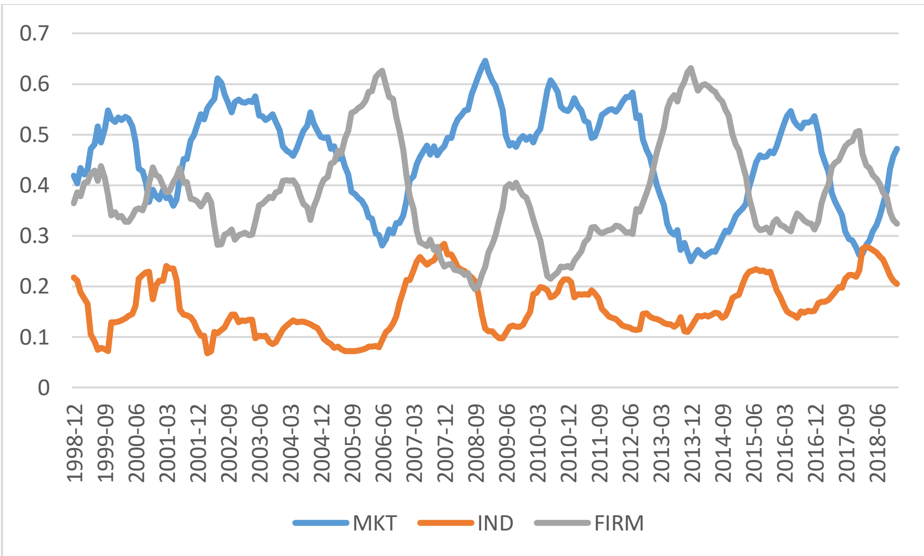


Figure 4.4: **Proportion of volatility components.**

The proportion of volatility components (MKT, IND and FIRM) with backwards 12-month moving average process in each month over 1998 to 2018.



4.4 Time series behaviour of volatility components

In this section, we proceed to investigate the time-series behaviour of the three volatility series and identify the dynamic patterns and the determinants of the risen or fallen evidence of volatility series. We start by providing statistical information and time trend test of three volatility series, followed by the Granger-causality test, and then introduce them into Markov regime-switching system.

4.4.1 Descriptive statistics

Panel A of Table 4.1 presents the descriptive statistics of the monthly annualized volatility series of MKT, IND and FIRM, estimated from CLMX methodology. Consistent with Figure 4.1-4.3, the mean ($\times 10^2$) of MKT is highest as 7.038, followed by FIRM as 4.711, and is lowest for IND as 3.134. Panel B shows that MKT and IND are highly correlated as expected with a correlation coefficient of 0.811. FIRM, however, tends to be less correlated with the other two series, in which the coefficient with MKT is 0.342 and the coefficient with IND is 0.107. Panel C of Table 4.1 presents the autocorrelation feature of the three volatility components. The autocorrelation of FIRM is fairly higher than MKT and IND. We further perform unit root test by augmented Dickey and Fuller (1979) and the results are presented in panel D. The results reject the presence of a unit roots for all three volatility components at 1% level[15].

Table 4.1: Descriptive statistics

This table presents the descriptive statistics and trend test of monthly volatility components of annualized ($\times 12$) MKT, IND and FIRM estimated by CLMX approach over 1998 to 2018. Panel A reports the basic information of summary statistics. Panel B and Panel C report the information of correlation matrix and autocorrelation structure. Panel D reports the t statistics of augmented Dickey-Fuller test for unit root test based on the regressions with a constant, and the regressions with a constant and a trend. Finally, Following CLMX and Bunzel and Vogelsang (2005), we test the time trend for each volatility series based on the benchmark model: $y_t = b_0 + b_1 t + \mu_t$, where y_t is the variable of interest and t is a linear time trend, the results of which are reported in Panel E. The 5% critical value (2-sided) for t-DAN is 2.052.

Panel A. Summary statistics							
	Mean	Min	25th	Median	75th	Max	Std.
MKT ($\times 10^2$)	7.038	0.381	2.339	3.629	7.044	152.174	11.904
IND ($\times 10^2$)	3.134	0.095	0.64	1.113	2.426	218.089	14.045
FIRM ($\times 10^2$)	4.711	0.916	1.911	3.034	5.934	41.416	4.759

Panel B. Correlation matrix			
	MKT	IND	FIRM
MKT	1	0.811	0.342
IND		1	0.107
FIRM			1

Panel C. Autocorrelation structure			
	MKT	IND	FIRM
ρ_1	0.26	0.084	0.549
ρ_2	0.232	0.02	0.42
ρ_3	0.177	0.013	0.288
ρ_4	0.169	0.028	0.231

[15] The one percent critical values for the unit root test are -3.47 with a constant, and -4.01 with both constant and a trend.

ρ_6	0.158	0.017	0.122
ρ_{12}	0.076	0.005	0.001
Panel D. Unit root test			
	MKT	IND	FIRM
Constant(t)	-7.998	-10.501	-6.272
Constant and trend (t)	-7.981	-10.479	-6.28
Panel E. Trend test			
	MKT	IND	FIRM
Linear trend ($\times 10^5$)	1.527	0.582	5.935
t-statistics	0.148	0.048	1.443
t-Dan	0.075	0.04	0.556

Whether there is a trend of idiosyncratic volatility in U.S. stock market has aroused the interests of a number of research (Campbell et al., 2001; Brandt et al., 2010). This is because the increased trend of idiosyncratic volatility would be beneficial to investors who are seeking for portfolio diversification. In this chapter, we aim to test whether there is any evidence that China's incremental reforms have acted to alleviate informational asymmetries (Chap. 2), which have previously been through to result in little evidence of idiosyncratic volatility. Growth in the idiosyncratic component of volatility overtime could be seen as consistent with the reforms successfully improving firm-specific information available to traders, reducing past informational asymmetries and facilitate the ability of informed investors to benefit from diversifying holdings to reduce risk.

To formally test the trends of volatility series, we follow CLMX and use Bunzel and Vogelsang (2005) linear time trend test[16]. The benchmark model is as:

$$y_t = b_0 + b_1 t + \mu_t, \tag{4-17}$$

where y_t is the test variable and t is the time trend. The "t-DAN" statistic developed by Bunzel and Vogelsang (2005) is used to test for the null hypothesis of $b_1 = 0$, in which the suffix "Dan" denotes the use of "Daniel Kernel" to non-parametrically estimate the error variance in the test. We also use AR (1) model to prewhiten the data as Bunzel and Vogelsang (2005) shows the better performance of the finite sample properties in the test for prewhitening.

Panel E of Table 4.1 shows the results of t-DAN trend test, in which we cannot reject the null hypothesis that there is no trend observed for all three volatility measures (MKT, IND and

[16] Despite CLMX use Vogelsang's (1998) linear time trend test, Bunzel and Vogelsang (2005) develop a test that retains the good size properties of the Vogelsang's (1998) test, but it has better power (both asymptotically and in finite samples).

FIRM). The evidence of no long-term trend in the time series behaviour of idiosyncratic volatility is supportive to findings of Nartea et al. (2013) using Fama-French three factors model to measure aggregate idiosyncratic volatility.

4.4.2 Granger causality

Next, we are interested in whether the three volatility components help to forecast each other. Table 4.2 investigates this question by using the Granger causality test in both bivariate and trivariate systems. Panel A reports the p-values for bivariate VARs whereas Panel B reports the p-values in trivariate VAR where includes all three volatility component series. The lag length of VARs is selected from Akaike information criterion (AIC). In a bivariate system, FIRM tends to Granger-cause both MKT and IND whereas IND tends to Granger-cause only MKT. MKT, however, does not help to predict IND or FIRM. The predictive power of FIRM on MKT and IND also survives in trivariate VAR as Panel B shows. However, IND fails to predict MKT in trivariate case. Further, both MKT and IND tend to Granger-case FIRM in trivariate VAR. Unlike CLMX (2001) who reports that MKT tends to lead the other volatility series in U.S. stock market, our findings suggest that the FIRM is helpful to forecast the other volatility components.

Table 4.2: **Granger causality**

This table presents the p-values of Granger causality VAR tests across MKT, IND and FIRM estimated by CLMX approach over 1998 to 2018. Panel A reports the results in bivariate VAR system for each pair while Panel B reports the results in a trivariate VAR system. The null hypothesis is the lags 1 through l of series indicated in the row do not help to forecast the series indicated in the column. For each VAR system, the lag length l is chosen using the AIC information, and is reported in parentheses.

Panel A. Bivariate VAR			
	MKT(t)	IND(t)	FIRM(t)
MKT(t-l)		0.231	0.415
		(5)	(5)
IND(t-l)	0.035		0.409
	(5)		(2)
FIRM(t-l)	0.005	0.034	
	(5)	(2)	
Panel B. Trivariate VAR			
	MKT(t)	IND(t)	FIRM(t)
MKT(t-l)		0.140	0.002
IND(t-l)	0.054		0.001
FIRM(t-l)	0.009	0.011	
	(5)	(5)	(5)

4.4.3 Regimes switching

A number of studies point out that the results of trend tests can be affected by the selection of starting and ending time points (e.g. Bakaert et al., 2012; Nartea et al., 2013). To solve this question, Bakaert et al. (2012) investigate the aggregate volatility in 23 developed markets and do not find the evidence of upward trends after extending the samples to 2008. Importantly, they suggest that the early findings of upward trend of idiosyncratic volatility in U.S. stock market can be driven by the selection of starting and ending observed time points. In other words, if the test period starts from a low volatility point and ends with a high volatility point, it is easy to identify the positive trend in the trend test. Therefore, Bakaert et al. (2012) fit a Markov regime-switching model with a first-order autocorrelation structure for monthly idiosyncratic volatility series and find the idiosyncratic volatility is well described by a stationary regime-switching process with occasionally shifts to high-variance regime. Using the similar regime-switching model, Garcia et al. (2014) define the aggregate cross-sectional variance (CSV) and find the CSV is countercyclical and becomes high and variable when economic growth subsides. Another related study by Nartea et al. (2013) investigates the time behaviour of monthly aggregate volatility, constructed from Fama-French (1993) model, in Chinese stock market from 1994 to 2011, and does not find the long-term trend of idiosyncratic volatility. Instead, the idiosyncratic volatility is also described by autoregressive process with regime shifts, and further coincide with structural market reforms.

In line with Garcia et al. (2014), we fit the Markov regime-switching model with a first-order autocorrelation structure (AR (1)) to identify time series switching behaviour for three volatility components. As idiosyncratic risk is documented to be volatile in the rise and fall in U.S. stock market (Brandt et al., 2010), we aim to investigate whether this is also the case in Chinese stock market and if so, who drives to this time-series behaviour. In this model, two regimes are indexed by a discrete state variable (S_t), following a Markov-chain process with constant transition probabilities. Therefore, the model is specified as follows:

$$x_t - \mu_i = \varphi\left(x_t - \mu_j\right) + \sigma_i e_t, \quad \text{i, j} \in \{1,2\} \tag{4-18}$$

where x_t is the time series of monthly three volatility components, which are MKT, IND, and FIRM; μ_i is the current regime and μ_j represents the past regime.

The transition probability matrix ϕ includes each 2×2 probability that represents $P[S_t = i | S_{t-1} = j]$, with $\text{i, j} \in \{1,2\}$:

$$\phi = \begin{pmatrix} p & 1-p \\ 1-q & q \end{pmatrix}.$$

Therefore, the model involves a total of 7 parameters, $\{\mu_1, \mu_2, \sigma_1, \sigma_2, \varphi, p, q\}$.

Table 4.3 presents the results for each time series of volatility components (MKT, IND and FIRM). For all three volatility series, the low-mean, low-variance regimes display a higher probability of remaining in the same state. The regime 2 also has higher volatility than regime 1 for all MKT, IND and Idiosyncratic volatility. Thus consistent with Bekaert et al. (2012) and Nartea et al. (2013), we find that idiosyncratic volatility in Chinese stock market can be characterized by a stationary autoregressive process that occasionally switches between high and low volatility regimes. Further, the similar patterns also appear for market and industry volatility.

Table 4.3: **Regimes switching model**

This table reports the parameter estimates of the regime-switching model specified from equation (4-18) for the volatility series of MKT, IND and FIRM over 1998 to 2018, estimated from CLMX approach.

	MKT	IND	FIRM
μ_1	0.031	0.013	0.022
μ_2	0.176	0.155	0.082
σ_1	0.015	0.01	0.008
σ_2	0.19	0.365	0.055
φ	0.049	0.008	0.332
p	0.894	0.928	0.914
q	0.716	0.521	0.881

Figure 4.5 shows the smoothed probabilities of being in the high-variance regime (regime 2) for time series of all three components over 1998 to 2018. Panel A shows that the market volatility is in low volatility regime for the majority of study periods except for two evident high volatility regimes periods of market crashes around 2007-2008 and 2015-2016. The industry volatility in Panel B shows a similar pattern whereas appearing to be more stable in a low volatility regime compared to market volatility.

We are particularly interested in the idiosyncratic volatility series as presented in Panel C of Figure 4.5. Similar to market and industry volatility, idiosyncratic volatility is also in high volatility regime during market crash periods. However, idiosyncratic volatility shifts more frequently between high and low volatility regimes than market and industry volatilities in other study periods, which is consistent with the unstable feature document earlier.

Similar to Nartea et al. (2013), we find idiosyncratic volatility tends to stay in high volatility regime over the majority of periods before market liberalization, the reform of which allows domestic investors to purchase B shares at the end of 2000. Afterward, the idiosyncratic volatility stays in the low volatility regimes until the middle of 2001 that shifts in the high volatility regime and ends in the middle of 2002. The starting time point of this one-year high volatility regime duration may be related to the market index hitting a peak in June of 2001 and afterward keeping a decreasing tendency until early 2002. Since November of 2002 when the QFII scheme was launched, allowing foreign institutional investors to invest in A-shares, the idiosyncratic volatility is back to the low volatility regime until the third quarter of 2004. It shifted again to the high volatility regime since Sep 2004 along with the implementation of reform[17], suggesting the reform of split-share structure led to a consequent increase in the variance of idiosyncratic volatility. The idiosyncratic volatility shifts back to low volatility regime since the end of 2009 after the financial crisis and stays in this regime for most of the period until in the middle of 2012, which is consistent with Nartea et al. (2013).

However, the idiosyncratic volatility stays in the high variance regime in most of the period from the middle of 2012 until the middle of 2016 when the stock market crash of 2015-2016 ends. The shift to high variance regime around 2013 may be related to a number of events related to i) downward tendency of market index, in which Shanghai composite index hits the bottom lower than 2000 again in year 2013 since year 2009; ii) regulators had suspended IPOs on Chinese stock markets for more than one year in 2013; iii) Everbright Securities hit with record fine for trading error in Aug 16, 2013, leading to abnormal volatilities across related firms. In more recent period since July 2016, we observe that the idiosyncratic volatility stably stays in low variance regime, which may be at least partially related to a set of steps in Chinese stock market toward financial market liberalization (e.g. Shanghai-Hong Kong Stock Connect, Shenzhen-Hong Kong Stock Connect and inclusion of MSCI Emerging Markets Index[18]).

In sum, results from Table 4.3 and Figure 4.5 are consistent with the findings of the trend test that all the three volatility series show no long-term trend. Instead, the volatility series are characterized by an autoregressive process with regime shifts. Further, the shifts of the high volatility regime of market and industry volatilities are mainly related to occurrence of financial crisis. The regime shifts of idiosyncratic volatility, however, not only related to

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[17] China Securities Regulatory Commission announced '*Circular of China Securities Regulatory Commission on Distributing the Measures for the Administration of the Share-trading Reform of Listed Companies'* at Sep 4, 2005, which denotes the implementation of split-share reform in Chinese stock market.

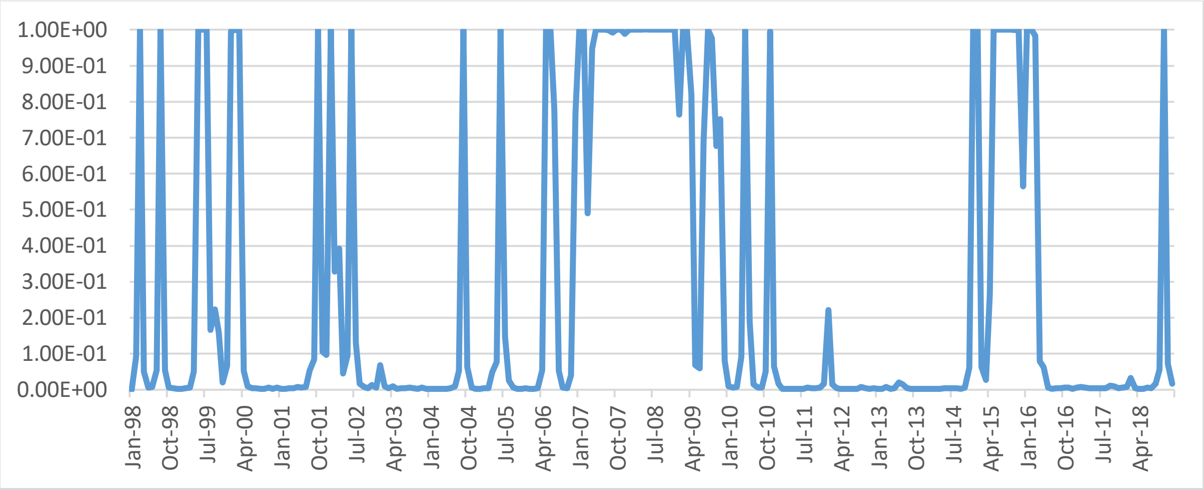
[18] Shanghai-Hong Kong Stock Connect and Shenzhen-Hong Kong Stock Connect schemes are launched at Nov 2014 and Dec 2016, allowing investors in each market to trade shares on the other market. Chinese stock markets has been taking active steps towards the inclusion of MSCI Emerging Markets Index and MSCI started to partially include China large-cap A shares in the MSCI Emerging Markets Index on May 31st, 2018.

financial crash but also coincide with structural market reforms and the movement of market index.

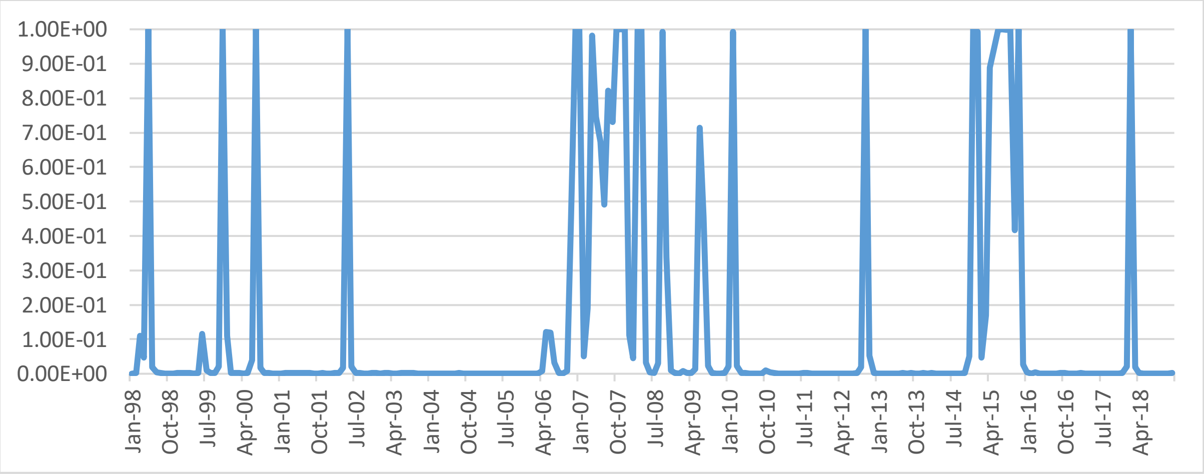
Figure 4.5: **Regime probabilities for MKT, IND and FIRM.**

The regime probabilities of market, industry and idiosyncratic volatilities are estimated from equation (4-17).

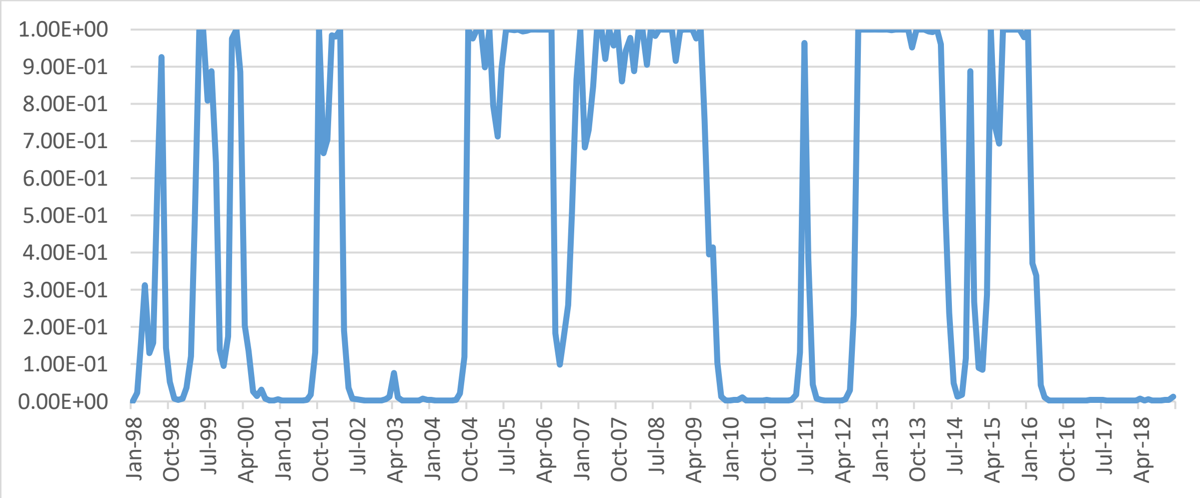
Panel A. Market volatility



Panel B. Industry volatility



Panel C. Idiosyncratic volatility



4.5 Determinants of idiosyncratic volatility

We have documented that idiosyncratic volatility of stock returns in Chinese stock markets are characterized by an autoregressive process with regime shifts. Further, compared to market and industry volatility, idiosyncratic volatility is more frequent in switching between high and low variance regimes. It is natural to ask the question that who drives to the change of idiosyncratic volatility in stock market behaviour, institutional investors or retail investors. We proceed to investigate the unexplored question in Chinese stock market.

4.5.1 Hypotheses development

The proposed explanations for this question include the institutional ownership (Bennett, Sias, and Starks 2003; Xu and Malkiel, 2003; Che, 2018) or retail trading activity (Brandt et al., 2010; Foucault et al., 2011; Nartea et al., 2013).

With respect to two close literature, Brandt et al. (2010) show the increased idiosyncratic volatility, documented by CLMX (2001) over the period from 1962 to 1997 in U.S. stock market, is episodes rather than time trend, in which the idiosyncratic volatility falls back to pre-1990s levels in 2003. Brandt et al. (2010) further show an increase and subsequent reversal phenomenon of idiosyncratic volatility is at least partially associated with retail investors. Another study by Nartea et al. (2013) investigates the time-series behaviour of idiosyncratic volatility in Chinese stock market and finds no evidence of a long-term trend. The aggregate idiosyncratic volatility is described as by autoregressive process with regimes shift associated with structural market reforms. In addition, due to the retail dominance in stock trading in Chinese stock market, they also present supportive evidence that the episodic idiosyncratic volatility is associated with retailing trading.

The question of whether institutional investors or individual investors are responsible for the changes of idiosyncratic is our key research question in this section. Despite Nartea et al. (2013) conjecture that retailing investors might be responsible for the changes of idiosyncratic volatility in Chinese stock market due to the dominance of retail trading, the formal tests related to this question has not been examined. Nevertheless, previous studies have documented that the institutional investors in Chinese stock market are momentum traders while Chinese individual investors at large are contrarian investors (Ng and Wu, 2007). The momentum trading by institutional investors drives the stock price apart from intrinsic value, leading to higher idiosyncratic volatility. In addition, a number of recent studies show the destructive trading behaviour of institutional investors in Chinese stock markets. Chen et al. (2019) show large investors in Chinese stock markets play the destructive market behaviour from 2012 to 2015 by conducting pump-and-dump strategy for price-limit-hitting stocks, contributing to a destabilizing effect in Chinese stock market. Darby et al. (2019) use cash flow data of the largest trading group as the proxy for institutional trading from 2010 to 2017, and show that the institutional investors exacerbate the extreme market movement days in Chinese stock market. We thereby test the following hypothesis:

Hypothesis 4.1. Institutional investors drive to the idiosyncratic volatility of stock return in Chinese stock markets.

Brandt et al. (2010) also show that idiosyncratic volatility in U.S. stock market is strongly related to low-price stocks and the stocks of which are held by proportionally more by retail investors than institutional investors. This is because institutional investors tend to hold high-priced stocks for not only prudence reasons but also the less per share trading costs compared to actively trades on large positions in low-priced stocks. Therefore, we also expect the idiosyncratic volatility is high for the high-price stocks which are held by proportionally more by institutional investors, and test the following hypothesis:

Hypothesis 4.2. Idiosyncratic volatility of stock return is positively associated with stock price in Chinese stock markets.

4.5.2 Model specification

Following CLMX and Brandt et al. (2010), we use daily stock returns to construct monthly idiosyncratic volatility for each stock as:

$$IV_{it}^{CLMX} = \sum_{s \epsilon t} \epsilon_{is}^2, \quad (4\text{-}19)$$

where IV_{it}^{CLMX} is the idiosyncratic volatility for stock i in month t.

In order to identify the question of whether the institutional investors or retail investors drive to the idiosyncratic volatility, we investigate the trading behaviour of institutional investors by the perspectives of both institutional holding and institutional trading in a given month for a specific stock. This is because only using the quarterly institutional ownership data may conceal important details about the undisclosed short-term activities, see in Campbell, et al. (2009) and Boehmer and Kelley (2009) among others. Darby et al. (2019) further demonstrate that the institutional ownership may not be an appropriate proxy for institutional trading. Following Darby et al. (2019), we also use the cash flow data of the largest trading group for the information of institutional trading.

Similar to the model framework by Brandt et al. (2010), Che (2018) and Xie et al. (2019), we test the Hypothesis 4.1 and Hypothesis 4.2 by specifying the following model using Fama and MacBeth (1973) estimation:

$$\mathrm{Log}(\mathrm{IV}_{i,t}) = \alpha + \beta_1 Log(1 + INSTITUTION_{i,t}) + \beta_2 ITP_{i,t} + \beta_3 \mathrm{Log}(\mathrm{PRICE}_{i,t}) + \beta_4 \mathrm{Log}(\mathrm{IV}_{i,t-1}) + \beta_5 SIZE_{i,t} + \beta_6 TURNOVER_{i,t} + \beta_7 BTM_{i,t} + \beta_8 ROA_{i,t} + \beta_9 LEV_{i,t} + \beta_{10} PRETURN_{i,t} + \varepsilon_{i,t}, \quad (4\text{-}20)$$

where $\mathrm{Log}(\mathrm{IV}_{i,t})$ is the dependent variable, referring to the natural logarithm of idiosyncratic volatility in month t for firm i; the variables of key interest are $INSTITUTION_{i,t}$, referring to the percentage of shares held by institutional investors of stock i for the most recent quarter relative to month t; $ITP_{i,t}$, referring to the institutional trading proportion calculated from the total institutional trading volume divided by total market trading volume in month t for stock i, and $PRICE_{i,t}$ is the share price of stock i in month t. Thus, the positive coefficients of β_1 and β_2 translate Hypothesis 4.1, and the positive coefficient of β_3 translates Hypothesis 4.2; the other control variables included firm size ($SIZE_{i,t}$), turnover ratio ($TURNOVER_{i,t}$) calculated from the trading volume divided by the total share outstanding, book-to-market ratio ($BTM_{i,t}$), return on asset ($ROA_{i,t}$), leverage ratio ($LEV_{i,t}$) calculated from debt and asset value, and past 12-month stock returns ($PRETURN_{i,t}$). Moreover, similar to Tian et al. (2018), we also measure the segregate ownership of institutional investors classified into four groups as i) mutual fund (FUND); ii) qualified foreign institutional investors (QFII); iii) financial institutional investors (FINANCE), which includes insurance companies, broker dealers, banks, fund management companies, among others; and iv) other institutional investors (OTHER), which includes pension funds, company annuity funds and other legal entities. In particularly, the variable of lagged idiosyncratic volatility ($\mathrm{Log}(\mathrm{IV}_{i,t-1})$) is contained in the model the alleviate the autocorrelation concerns of the persistence of monthly idiosyncratic volatility.

We include selected firm specific variables in the regressions as conditioning variables. For example, we would not want to make potentially invalid inferences on the impact of institutional trading if the results were in fact impacted by omitted variable bias, say if institutional trading were acting as a proxy for the firm size because institutional investors prefer to trade in stocks with large size (e.g. Lakonishok et al., 1992). Turnover ratio is included for the liquid factor as institutional investors are documented to prefer liquid stocks (Falkenstein, 1996; Gompers and Metrick, 2001). Malkiel and Xu (2003) show that idiosyncratic volatility is positively associated with future growth opportunities. Companies with higher market value relative to book value correspond to high future growth opportunities, and may cause speculative exuberance about the firm, leading to higher idiosyncratic volatility (Brandt et al. 2010). Therefore, the book-to-market ratio is expected to be negatively related to idiosyncratic volatility. Return-on-asset (ROA) is included for the measure of firm performance as Shan et al. (2014) document that firms with lower ROA are expected to have greater stock return fluctuation. Moreover, a firm with high financial leverage (the ratio of total debt divided by total asset) could be more risky, thereby having more stock return volatility (e.g. Shan et al., 2014; Xie et al. 2019). Finally, the past return variable is controlled for the known effects of past returns on the trading behaviour of investors (e.g. Barber and Odean, 2008) such as herd behaviour, contrarian strategy, and exhibition of the disposition effect.

4.5.3 Findings

Based on the availability of institutional trading data from 2009 to 2018, we first examine the mean statistics of the key variables in our study while sorting the all firm-month observations into ten deciles based on the proportion of institutional trading (see Table 4.4). In contrast with the findings by Brandt et al. (2010) in U.S. stock market, we find that institutional trading proportion is stronger among stocks that have higher idiosyncratic volatility, suggesting idiosyncratic volatility in Chinese stock market is related institutional trading activities. Further, stocks with higher institutional trading proportion also have higher, on average, firm size, stock price, institutional ownership and turnover ratio. Specifically, stocks with institutional trading proportion in the top five deciles have typically stock price above 15 RMB yuan. The results suggest the large-price stocks are more proportionally held by institutional investors.

Table 4.4: **Stock characteristics sorted on institutional trading**

This table reports the mean of monthly characteristics (institutional trading proportion measured as the institutional trading volume divided by whole market trading volume, idiosyncratic volatility measured by CLMX methodology, firm size, stock price, percentage of shares owned by institutional investors, turnover ratio measured as the trading volume divided by all shares outstanding), conditional on degree of institutional trading, over period from 2009 to 2018.

	Mean	IVOL (%)	Size (RMB)	Price	Ownership	Turnover
Low(D1)	0.62%	0.74	3196.91 m	11.25	30.74%	28.51%
D2	2.24%	0.86	4189.47 m	12.65	31.76%	38.70%
D3	3.83%	0.91	5076.38 m	13.57	32.90%	42.99%
D4	5.60%	1.02	6010.53 m	14.2	34.23%	46.61%
D5	7.61%	1.12	6941.44 m	14.94	35.40%	50.42%
D6	10.06%	1.25	8171.65 m	15.66	36.54%	54.82%
D7	13.21%	1.44	9918.97 m	16.58	37.88%	59.55%
D8	17.58%	1.83	13355.61 m	17.68	39.57%	64.84%
D9	24.66%	3.07	21528.3 m	19.5	41.39%	73.47%
High(D10)	43.56%	13.1	59070.65 m	22.89	44.29%	83.44%

Table 4.5 shows the findings in the multivariate framework using Fama-MacBeth monthly cross-sectional regressions. Columns 1 to 4 include the full samples without institutional trading variables while column 5 and 6 focus on the period of 2009-2018 including the institutional trading information based on the data availability.

The question of whether institutional investors drive to idiosyncratic volatility (Hypothesis 4.1) is our key interest in this section and we use both institutional ownership and institutional trading to investigate the trading activities of institutional investors. We first look at the impact of share percentage of institutional ownership on idiosyncratic volatility of stock returns. In our full sample (column 1) or subsample analysis (column 2 and 3), the coefficients between idiosyncratic volatility and institutional ownership are all significantly positive at 1% significant level. Further, compared to the early sub-period of 1998-2008, the coefficient estimated from the recent sub-period of 2009-2018 is greater, indicating the effect of institutional ownership on idiosyncratic volatility is stronger in the recent 10 years. Compared to the column 3, the regression in column 4 further segregates the institutional ownership into four groups, i.e. mutual fund, QFII, financial and other institutions, and shows that the institutional ownership held by mutual fund have the greatest impact on idiosyncratic volatility while the holding by foreign investors is insignificantly related to idiosyncratic volatility. In column 5 and 6 when including institutional trading measures as additional explanatory variable, we find that institutional trading proportion (ITP) has a significantly positive coefficient estimate (coefficient estimates = 3.125 and 3.126, t-statistics = 41.78 and 41.799), which indicates that the degree of institutional trading has an incremental effect on the level of idiosyncratic volatility. Moreover, the relationship between institutional trading and idiosyncratic volatility is stronger than that institutional ownership, suggesting the trading by institutional investors has a stronger impact on idiosyncratic volatility than the shareholding held by institutional investors. Our results are consistent with the view that institutional investors in Chinese stock market are momentum traders, the herding behaviour of which drives the stock price further away from fundamental value, leading to higher firm-specific volatility. The findings also supportive with the recent study institutional investors play a destructive role in Chinese stock market, in which higher institutional trading is associated with higher firm-specific volatility. To summarize, our results are supportive of Hypothesis 4.1 that institutional investors drive to the idiosyncratic volatility of stock returns in Chinese stock market.

Table 4.5 also reports the coefficients of stock price which is another key interest of Hypothesis 4.2. We find the coefficients of stock price are all positive and significant at 1% significance level, which is consistent with Hypothesis 4.2 that the high idiosyncratic volatility is associated with a high stock price. The finding is also supportive to the relation between idiosyncratic volatility and trading by institutional investors because if institutional investors find high-priced stocks attractive and engage more trades in those stocks, institutional investors could influence the idiosyncratic volatility patterns of those stocks.

In addition, the coefficients of one-month lagged idiosyncratic volatility are significantly positive which is consistent with the volatility persistence conjecture. Firm size is negatively and significantly associated with idiosyncratic volatility, suggesting smaller firms are more volatile than larger firms, conditional on the stock price unchanged. Likewise, stocks with higher volume turnover tend to exhibit higher idiosyncratic volatility. Consistent with expectation, book-to-market ratio is significantly and negatively related to idiosyncratic volatility, suggesting the companies with higher growth opportunities tend to attract more speculative exuberance and thereby having higher idiosyncratic volatility. Furthermore, as expected, companies with higher idiosyncratic volatility is associated with lower return on asset and higher financial leverage ratio. Interestingly, the coefficient of financial leverage become insignificant when we introduce variables of the institutional trading proportion in the regression, reflecting the fact that institutional investors tend to trade on risky stocks with high financial leverage.

Table 4.5: Aggregated institution and idiosyncratic volatility (1998-2018)

This table reports estimate from monthly Fama-MacBeth cross-sectional regressions over full period or sub-periods over 1998 to 2018, in which the dependent variable is the natural logarithm of idiosyncratic volatility using CLMX estimation. The independent variables include level of either aggregate or segregated institutional ownership for most recent quarter, institutional trading proportion (total institutional trading volume divided by the market volume), stock price, lagged idiosyncratic volatility, firm size measured as the natural logarithm of firm market capitalization, financial leverage (total debt to total asset), turnover ratio measured as the total trading volume divided by all shares outstanding, book-to-market ratio, return on asset ratio, and past returns from last 12-months.

	Dependent variable: Log (IV)					
	(1)	(2)	(3)	(4)	(5)	(6)
	1998-2018	1998-2008	2009-2018	2009-2018	2009-2018	2009-2018
Log(1+INSTITUTION)	0.465***	0.327***	0.610***		0.481***	
	(8.540)	(3.223)	(21.527)		(20.195)	
Log(1+FUND)				0.684***		0.578***
				(10.093)		(7.686)
Log(1+QFII)				-0.102		0.242
				(-0.549)		(1.269)
Log(1+FINANCE)				0.352***		0.318***
				(5.830)		(5.975)
Log(1+OTHER)				0.582***		0.453***
				(22.083)		(20.596)
ITP					3.125***	3.126***
					(41.780)	(41.799)
Log(Price)	0.085***	0.060***	0.111***	0.096***	0.137***	0.125***
	(8.212)	(3.233)	(14.903)	(13.293)	(18.175)	(18.078)
Log (lagged IV)	0.229***	0.209***	0.250***	0.247***	0.239***	0.237***
	(33.806)	(18.100)	(39.949)	(39.752)	(42.602)	(42.548)
SIZE	-0.071***	-0.080***	-0.062***	-0.067***	-0.292***	-0.296***
	(-11.513)	(-7.326)	(-11.573)	(-12.957)	(-38.109)	(-38.554)
TURNOVER	1.107***	1.498***	0.696***	0.701***	0.492***	0.495***
	(21.394)	(17.759)	(27.792)	(27.889)	(22.979)	(23.181)
BTM	-0.126***	-0.196***	-0.052***	-0.050***	-0.065***	-0.064***
	(-7.554)	(-6.306)	(-16.169)	(-15.454)	(-20.764)	(-20.279)
ROA	-1.093***	-1.350***	-0.823***	-0.842***	-0.685***	-0.703***
	(-6.959)	(-4.574)	(-10.048)	(-10.266)	(-9.615)	(-9.849)
LEV	0.125***	0.191***	0.055***	0.054***	0.003	0.003
	(6.309)	(5.137)	(8.462)	(8.454)	(0.440)	(0.460)
PRETURN	0.088***	0.046	0.131***	0.129***	0.073***	0.072***
	(3.997)	(1.183)	(7.479)	(7.411)	(4.877)	(4.817)
Constant	-2.907***	-2.787***	-3.032***	-2.903***	1.836***	1.940***
	(-19.847)	(-10.553)	(-26.315)	(-26.149)	(11.810)	(12.391)
Observations	348,812	76,763	272,049	272,049	272,049	272,049
R2	0.559	0.664	0.523	0.525	0.579	0.582
Note:	*p<0.1; **p<0.05; ***p<0.01					

Finally, we find that idiosyncratic volatility is positively associated with past returns, particularly in the analysis of the recent ten years of 1998-2018, which suggests the stocks with high past returns are more likely to attract the attention of speculative investors in Chinese stock market, leading to higher idiosyncratic volatility.

4.5.4 Robustness check

Bekaert, Hodrick, and Zhang (2009) show that the unit beta restrictions in CLMX (2001) approach is not able to match the stock return co-movements. We therefore also consider the other measure of idiosyncratic volatility for robustness check by using classic CAPM and Fama-French (1993) three factors model (e.g. Ang et al., 2009; Xie et al., 2019).

We first consider the estimation of idiosyncratic volatility from CAPM model as follows:

$$R_{jt} = \alpha_{jt} + \beta_{mt} R_{mt} + \mu_{jt}^{CAPM}, \tag{4-21}$$

where R_{jt} is the daily excess return for stock j in month t, and R_{mt} is the daily excess market return in month t. μ_{jt}^{CAPM} denotes the daily residual estimated from CAPM model for stock i in month t and idiosyncratic volatility estimated from CAPM model is defined as $IV_{jt}^{CAPM} = \sqrt{Var(\mu_{jt}^{CAPM})}$.

We also consider the estimation of idiosyncratic volatility from Fama-French three factors model as follows:

$$R_{jt} = \alpha_{jt} + \beta_{1t} MKT_t + \beta_{2t} SMB_t + \beta_{3t} HML_t + \mu_{jt}^{FF}, \tag{4-22}$$

where R_{jt} is the daily excess return for stock j in month t. Here, the variable MKT represents the excess return on market portfolio, SMB is the size factor and HML is the value factor. Likewise, the idiosyncratic volatility estimated from Fama-French three factors model is defined as $IV_{jt}^{FF} = \sqrt{Var(\mu_{jt}^{FF})}$.

Table 4.6 shows the regression results of robustness check when the idiosyncratic volatility of stock return is estimated from CAPM model (column 1 and 2) or Fama-French three factors model (column 3 and 4). Compared to Table 4.5 in which idiosyncratic volatility is estimated from CLMX approach, the results in robustness checks are both quantitatively and qualitatively similar. In sum, our study provides strong evidence that institutional investors drive to the idiosyncratic volatility in Chinese stock market, the results of which are also robust using the alternative measure of idiosyncratic volatility.

For another robustness check, we also regress idiosyncratic of volatility by all three measures on the proportion of retail trading (RTP) over 2013 to 2018 based on the data availability. Similar to Brandt et al. (2010), we obtain the cash flow data by the smallest trading group (trading size less than 50,000 RMB) as the proxy for retail trading. Therefore, the retail trading proportion is constructed by the retail trading volume divided by total market volume. We find the coefficients of RTP are significantly negative in all regression cases, indicating the trading activities by retail investors reduce the idiosyncratic volatility in Chinese stock market. All the other findings are quantitatively and qualitatively similar. The results can be accessed in Appendix E.

Table 4.6: Robustness check (2009-2018)

This table reports estimate from monthly Fama-MacBeth cross-sectional regressions over sub-periods over 2009 to 2018. The dependent variables are idiosyncratic volatility estimated from CAPM model in equation (4-26) or Fama-French three factors model in equation (4-27). All other variables are defined as before.

	Dependent variable:			
	$Log(IV^{MKT})$		$Log(IV^{FF})$	
	(1)	(2)	(3)	(4)
Log(1+INSTITUTION)	0.249***		0.281***	
	(20.528)		(23.694)	
Log(1+FUND)		0.438***		0.402***
		(11.389)		(9.953)
Log(1+QFII)		0.139		0.145
		(1.380)		(1.396)
Log(1+FINANCE)		0.134***		0.205***
		(5.286)		(7.600)
Log(1+OTHER)		0.231***		0.262***
		(20.237)		(23.604)
ITP	1.591***	1.589***	1.666***	1.664***
	(38.089)	(37.893)	(40.229)	(39.991)
Log(Price)	0.089***	0.078***	0.089***	0.079***
	(20.643)	(19.825)	(22.712)	(21.439)
Log (lagged IV^{MKT})	0.229***	0.225***		
	(40.482)	(40.333)		
Log (lagged IV^{FF})			0.208***	0.204***
			(36.280)	(36.293)
SIZE	-0.147***	-0.150***	-0.147***	-0.151***
	(-35.909)	(-37.065)	(-33.500)	(-34.518)
TURNOVER	0.264***	0.267***	0.274***	0.277***
	(24.285)	(24.510)	(25.614)	(25.855)
BTM	-0.022***	-0.021***	-0.028***	-0.027***
	(-16.210)	(-15.362)	(-19.248)	(-18.436)
ROA	-0.344***	-0.355***	-0.353***	-0.366***
	(-9.326)	(-9.555)	(-9.433)	(-9.662)
LEV	-0.009***	-0.009***	-0.0002	-0.0002
	(-2.830)	(-2.810)	(-0.057)	(-0.062)
PRETURN	0.032***	0.032***	0.040***	0.040***
	(4.123)	(4.085)	(5.106)	(5.061)
Constant	-0.357***	-0.285***	-0.561***	-0.481***
	(-4.157)	(-3.328)	(-5.995)	(-5.113)
Observations	272,049	272,049	272,049	272,049
R2	0.592	0.595	0.543	0.546
Note:	*p<0.1; **p<0.05; ***p<0.01			

4.6 Volatility patterns among industries

Despite so far we have examined aggregate IND volatility that contains the information about an average industry, there is a great deal of variation across industries, no matter regarding the differences of industry- or firm-specific volatility across industries. In this section, in order to further identify the source of high volatility in Chinese stock market from the view of individual industries, we first examine industry- and firm-specific volatilities of 15 largest industries separately according to the average market capitalization over the full sample.

In addition, Wang (2010) argues that far less attention has been paid to the other important contribution of CLMX (2001), as the analysis of stock return volatility at the industry level, because the industry-level analysis is important for the diversification of portfolios. Following Wang (2010), we further investigate the dynamic patterns of industry- and firm-specific volatilities across these industries to identify the most important lead indicators of industry- or firm-specific volatilities. As presented from the earlier sections, the idiosyncratic volatility not only exhibits more volatile feature but also tends to be the lead indicator to other volatility series relative to industry volatility on the aggregate level. Therefore, we are particularly interested in the dynamic patterns of firm-specific volatility across industries in this section and the results related to industry-specific volatility can be accessed in Appendix D.

4.6.1 Individual industries

Consistent with CLMX (2001) and Wang (2010), we alter the return composition in the following way, including a beta for each industry:

$$R_{it} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it}. \tag{4-23}$$

The volatility of industry return is thereby:

$$Var(R_{it}) = \beta_{im}^2 Var(R_{mt}) + \tilde{\sigma}_{it}^2, \tag{4-24}$$

where $\tilde{\sigma}_{it}^2$ is the variance of $\tilde{\varepsilon}_{it}$.

Then we also conduct the return composition for each firm in the similar fashion as:

$$R_{jit} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it} + \varphi_{jit}, \tag{4-25}$$

The weighted average idiosyncratic volatility in an industry is thereby:

$$\sum_{j \in i} w_{jit} Var(R_{jit}) = \beta_{im}^2 Var(R_{mt}) + \tilde{\sigma}_{it}^2 + \sigma_{\varphi it}^2, \tag{4-26}$$

where $\sigma^2_{\varphi it}$ is defined as before. The residuals of $\tilde{\varepsilon}_{it}$ in equation (4-23) and φ_{jit} in equation (4-25) are used to construct industry-specific and firm-specific volatility for individual industries.

Table 4.7 shows the manufacturing industry is the largest industry in our sample with an average weight of 39.3 percent in total market capitalization over the full sample, followed by the financial industry accounting for 21 percent in total market capitalization. The industry betas of most industries listed in Table 4.7 is around to unity, and the beta is highest for the mining industry whereas the lowest for the financial industry[19].

Panel A and Panel B of Table 4.7 display the industry- and firm-specific volatility across industries. On average, FIRM is substantially larger than IND. The mean of IND in the largest manufacturing industry is 1.302, which is much smaller than the mean of FIRM as 12.541, suggesting the manufacturing industry is the important source in aggregate volatility. The means of IND in second- and third-largest industry, as financial and mining industry, are 5.638 and 9.676, which are much higher than the mean of IND in most industries, indicating that the aggregate industry volatility in Chinese stock market may be sourced from financial and mining industry. Interestedly, despite the small shares (0.3 percentage) accounted in total market capitalization for scientific research and technical service industry, it exhibits the highest IND and FIRM compared to the other industries, reflecting the volatile feature of high-tech industry in Chinese stock market in terms of both industry and firm-specific volatility.

Although we documented that there is no trends for both IND and FIRM on average for aggregated data in the early section, we now ask the question whether this is due to i) the trade-off effect across industries, in which the volatility series of some industries exhibit upward trend whereas the others exhibit downward trend; or ii) no long-term trend in every industry. To solve this question, we first perform unit-root tests on all IND and FIRM. The augmented Dickey-Fuller (ADF) tests reject the unit-root hypothesis at 1% significance level for IND and FIRM in all industries. Next, we perform Bunzel and Vogelsang (2005) trend test for IND and FIRM in all industries, and the results are presented in the last columns in Panel A and Panel B of Table 4.7 respectively. Our results show that all the IND and FIRM in listed industries do not exhibit linear trend under the t-Dan test, suggesting that the findings of no

[19] Although we might theoretically see larger betas, it is not uncommon for low betas to be found (see for example the Table IV on page 21 in Campbell et al. (2001). We believe that in the Chinese sample used in my thesis potential explanations for these findings are likely to be the i) that a large number of newly listed stocks emerge during the sample periods we look at, which change the industry weights over time and ii) we focus on the broad industry classifications, which are dominated by the few very large industries. It is likely that some of the smaller industries may have greater systematic risks.

linear trends on aggregate IND and FIRM are due to the non-existing trend in each industry rather than the trade-off effect across industries.

Table 4.7: Volatility decomposition in each industry

This table reports the average weight, beta, mean industry-specific (Panel A) and firm-specific (Panel B) monthly volatility for the largest 15 industries in Chinese stock market over 1998 to 2018. There are four industries not included due to the scarcity of listed firms with less than ten in each industry. The industry volatility IND and idiosyncratic volatility FIRM have been annualized and multiplied by 100 for convenience.

Panel A. IND in main industries							
Industry	Weight	Beta	Mean	S.D.	ADF (t)	Trend	t-DAN
C	0.393	0.971	1.302	8.374	-10.658	1.364	0.161
J	0.21	0.839	5.638	38.848	-11.237	-43.901	-1.274
B	0.114	1.085	9.676	71.555	-9.972	-105.993	-1.399
K	0.046	0.998	3.758	12.095	-10.019	8.773	0.615
G	0.043	0.909	2.757	11.471	-10.723	-7.86	-0.7
I	0.042	0.998	4.709	18.848	-10.848	25.642	1.442
D	0.04	0.892	2.16	7.072	-9.499	0.076	0.009
F	0.034	0.961	1.898	8.29	-10.237	2.39	0.26
E	0.028	0.926	4.933	20.402	-10.406	-6.977	-0.304
R	0.01	0.967	17.108	165.467	-11.197	104.08	0.711
L	0.01	0.947	6.998	57.923	-11.199	-49.5	-0.983
A	0.008	0.918	13.833	93.905	-10.985	81.306	0.923
N	0.006	0.97	5.262	12.827	-10.469	-19.491	-1.447
S	0.005	1.041	3.285	10.3	-9.862	7.628	0.626
M	0.003	0.99	26.257	287.507	-10.893	-40.579	-0.151
Panel B. FIRM in main industries							
Industry	Weight	Beta	Mean	S.D.	ADF (t)	Trend	t-DAN
C	0.393	0.971	12.541	8.25	-5.339	17.947	0.574
J	0.21	0.839	7.936	26.051	-11.183	-41.65	-1.776
B	0.114	1.085	13.1	72.595	-10.051	-120.196	-1.551
K	0.046	0.998	11.922	13.1	-9.044	4.594	0.237
G	0.043	0.909	9.521	11.817	-9.23	-1.973	-0.111
I	0.042	0.998	13.986	19.03	-9.575	43.543	2.03
D	0.04	0.892	8.547	7.589	-6.987	-5.896	-0.366
F	0.034	0.961	11.673	6.852	-4.897	6.14	0.117
E	0.028	0.926	10.869	15.843	-9.16	-10.744	-0.488
R	0.01	0.967	26.156	173.446	-11.251	104.061	0.686
L	0.01	0.947	15.865	52.744	-11.008	-33.695	-0.719
A	0.008	0.918	18.395	87.681	-11.048	41.749	0.511
N	0.006	0.97	10.602	11.673	-8.829	-5.274	-0.318
S	0.005	1.041	11.711	6.131	-5.244	4.961	0.158
M	0.003	0.99	38.238	376.888	-11.062	-5.479	-0.016

Note: The classification of industry is based on the "Guidelines for the Industry Classification of Listed Companies" (2012 Revision) has been issued by China Securities Regulatory Commission (CSRC), in which A= Agriculture, forestry, animal husbandry and fishery; B= Mining industry; C= Manufacturing industry; D= Industry of electric power, heat, gas and water production and supply; E= Construction industry; F= Wholesale and retail industry; G= Transport, storage and postal service industry; H= Accommodation and catering industry; I=Industry of information transmission, software and information technology services; J= Financial industry; K= Real estate industry; L= Leasing and commercial service industry; M= Scientific research and technical service industry; N= Water conservancy, environment and public facility management industry; O= Industry of resident service, repair and other services; P= Education; Q= Health and social work; R= Industry of culture, sports and entertainment; and S= Diversified industries.

4.6.2 Dynamic patterns of volatility across industries

4.6.2.1 Methodology

Even if industry level volatility is considered, an aggregate measure of average industry volatility does not reveal much detail on the behaviour of individual industries (e.g. Ferreira and Gama, 2005; Wang, 2010).

In order to capture the dynamic patterns of IND and FIRM across industries, we apply Granger-causality tests in this section. Similar to Wang (2010), we estimate 210 four-variable multivariate VARs, each including two industry volatilities under studies, market volatility and a weighted average industry volatility[20]. The lag length of each VAR is selected from Akaike information criterion (AIC). The framework for testing Granger-causality is specified as follows:

Let $Y_t = [y_{1t}, y_{2t}, y_{3t}, y_{4t}]'$ denote a (4×1) vector consisting of the two testing volatility series of y_{1t} andy_{2t}, market volatility of y_{3t} and a weighted average volatility series of y_{4t} from other industries. The vector process Y_t can be modeled as the following autoregressive process with lag(s) p:

$$Y_t = \alpha + \sum_{l=1}^{p} \Gamma_l \, Y_{t-l} + \mu_t, \text{ t=1, 2, 3..., T,} \qquad (4\text{-}27)$$

where α is the vector of constants; Γ_l denotes the matrix of coefficients capturing the short-run dynamics with Y_{tl} with its ith row defined as $\Gamma_{li} = [\gamma_{li,1}, \gamma_{li,2}, \gamma_{li,3}, \gamma_{li,4}]$, and μ_t is the 4-vector of error terms satisfying the mean of zero and the covariance matrix $\sum$. Also, there is no correlation across time for μ_t.

In order to test whether series y_{2t} can help to forecast future values of y_{1t}, we implement Granger-Causality test by examining the following hypothesis in terms of parameter restrictions on model :

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[20] We also consider the VAR model that includes all 15 volatility component series across industries. The information criteria suggests VAR (1) due to the large dimension system, which is likely to underestimate the impacts of lags in Granger-causality test.

$$H_0: \gamma_{l1,2} = 0 \text{ for all l v.s. } H_1: \gamma_{l1,2} \neq 0 \text{ for some l}$$

Consistent to Wang (2010), we construct a Wald-type statistic which has a limiting distribution of χ_p^2 under the null.

4.6.2.2 Findings

The results of the multivariate Grange-causality test FIRM, as our key interest, across industries are presented in Table 4.8, and the results related IND can be accessed in Table D.1 of Appendix. The lag (s) selected from AIC in multivariate VAR systems can also be accessed in Table D.2 and Table D.3 in Appendix for industry- and firm-specific volatilities respectively.

Table 4.8: Dynamics of idiosyncratic volatility FIRM across industries

This table presents Granger-Causality test of dynamic volatility cross industries. An entry marked with symbol * reports the p-values of Granger-Causality test less than 5% significance level, suggesting that series indicated in the row helps to forecast the series indicated in the column. The notations of industry names are same as that in table 4.7.

	A	B	C	D	E	F	G	I	J	K	L	M	N	R	S
A				*			*								
B					*		*						*		
C	*	*		*	*		*	*	*	*		*	*		*
D							*			*					
E			*			*									
F	*	*		*	*		*	*		*		*			*
G													*		
I															
J							*								
K					*										
L															
M	*	*													
N							*								
R															
S	*		*	*		*	*	*		*			*		

The Granger-Causality test suggests that the FIRM in the manufacturing industry tend to lead most of the other firm-specific volatilities (11 of the other 13 industries). Further, FIRM in the wholesale and retail industry is also an important indicator as it helps to predict 9 other firm-specific volatility series. The FIRM of transport, storage and postal service industry, however, tend to be led by most of the other firm-specific volatility series (8 of the other 13 industries).

To summarize, the firm-specific volatility in manufacturing industry tends to be the lead indicator of the FIRM in other industries. In comparison with our previous finding, the results suggest the idiosyncratic volatility in manufacturing industry not only accounts for the largest proportion of aggregate idiosyncratic volatility but also tends to lead to idiosyncratic volatility in other industries.

4.7 Conclusion

In order to identify the sources of high volatility in China's stock market, this chapter decomposes the aggregate volatility at market, industry and firm level, and examines the volatility patterns at each level, particularly for firm volatility. As China's stock market become the second-largest stock market in the world, it is hoped the results contained in this chapter is beneficial to investors who seek for portfolio diversification at the international stock market or asset allocation for home-biased equity at industry-level diversification. Our study also provides insights for financial regulators to identify the potential risks in China's stock market.

In this chapter, we have shown that market volatility, on average, is highest among three volatilities. More importantly, we demonstrated that idiosyncratic volatility tends to lead the market and industry components of volatlity. These findings contrast with those for U.S. stock market. We suggest the difference can be attributed to the more opaque information environment that characterises the Chinese market. We then conducted a trend test which showed no evidence of a long-term trend in any of the volatility components. By fitting the Markov regime-switching model, we then showed that idiosyncratic volatility is less stable than the other components of volatility and switches more frequently between the high and low variance regimes.

We proceeded to identify the key determinants of the idiosyncratic volatility component in Chinese stock market by employing Fama-MacBeth cross-sectional regressions. We demonstrated that the idiosyncratic volatility is positively and significantly associated with stock prices, institutional ownership and the proportion of trading, conducted by institutional investors. Our results were shown to be robust to the other use of classic measures of idiosyncratic volatility. Moreover, investors' trading behaviour was shown to play a key role in determining the idiosyncratic risk in Chinese stock markets; in contrast to the retail trading effect documented in the U.S. stock market.

Finally, we further provided more details of idiosyncratic volatility through investigating each of the top 15 individual industries. No evidence was found for a long-term trend in idiosyncratic volatility in any of these industries. Interestingly, the idiosyncratic volatility of the manufacturing industry not only accounts for the largest proportion in the aggregate idiosyncratic volatility, but also leads the idiosyncratic volatility of other industries, suggesting the manufacturing industry might be the main source of idiosyncratic volatility in the Chinese stock market.

Overall, these results in this chapter provide insight into the volatility dynamics of the Chinese capital market, which are largely different with results usually documented in western markets. We hope these results will help to understand deeper on China's stock markets for global investors, researchers, regulators and financial analysts as a whole.

Chapter 5

5. Conclusion

Using a large firm-level dataset covered from 1998 to 2018, this thesis investigates the source of high volatility in Chinese stock returns and the relation with trading activity by institutional investors. As Chinese stocks have become increasingly popular with global investors on portfolio management in recent years, this thesis brings valuable insights into the better understanding of a rapidly growing emerging market, the background of which is distinctive to the typical Western market. Built on the methodology proposed by the literature on U.S. study, the thesis has incorporated the unique features of Chinese stock market, such as the substantial listed SOEs and price limit rules, into the study that are likely to affect the results. The results contained in this thesis are noticeably different from those in Western stock market due to the unique characteristics of Chinses stock market. It is hoped that the results contained in this thesis will be of interest to financial practitioners in understanding the sources and patterns of volatility in the Chinese stock market, and to financial regulators interested in the policy implications of improving the information environment in Chinese stock market.

The first essay (Chapter 2) has demonstrated that the volatility of China's stock returns tends to be greater, and to persist for longer, than is typical in 'western' markets. To the best of our knowledge, there has been no in-depth exploration of potential explanations on the drivers of volatility persistence. This is the gap in the literature that we have sought to address. This characteristic is initially documented using range based measures of volatility at the level of market indices. Although high volatility persistence has been identified in prior studies, there is no clear agreement as to why this is the case. Consistent with the earlier theoretical framework, Chapter 2 provides empirical evidence consistent with high volatility persistence being an outcome of the information environment that the majority of Chinese stock market investors operate in. It is generally accepted that the availability of transparent information relevant to the prospects of listed firms can speed up the dissemination of 'news' and contribute to speedier price adjustments when they are needed, resulting in less persistence in stock return volatility. So conversely, persistence in volatility may be the result of investors operating in a more opaque information environment. We are able to demonstrate that the persistence in firm level stock price volatility is positively associated with ownership concentration (having controlled for standard firm size, book to market ratio, turnover ratio, industry and year effects) and is highest when the largest shareholder is local government related. In order to examine the factors that are helpful to alleviate the information asymmetry, we go on to assess whether moves aimed at improving the information environment have had any significant impact on volatility persistence. In particular we look at i) the role played by growing numbers of financial analysts reporting on China's stock market and ii) the Chinese government's moves toward increasing institutional ownership of shares, when active institutions are large shareholders they should be able to monitor companies they invest in, reducing information asymmetries, reducing agency problems and maximizing shareholder value by virtue of their superior skills, resources and more sophisticated processing of information.

As China's stock market is growing rapidly in recent years, our results provide policy implication that the growing number of financial analysts and active institutional investors are helpful to alleviate the trading information environment. To the best of our knowledge, these findings, focusing on factors that influence the persistence of volatility in Chinese stock returns are entirely new. In addition, our these findings contribute to the insights to policymakers of the improvement of the information environment in China's stock market.

The second essay (Chapter 3) has examined the question of whether the trading activity by institutional investors or retail investors exacerbate the extreme market movements in China's stock market where price limit rule is imposed, and the impact of these trading activity on the post extreme days for price-limit-hitting stocks. Understanding the sources and patterns of market swings in China's stock market brings valuable insights to the risk management for financial practitioners as well as to the evaluations of the price limit role for policymakers in extreme market movement days. There are two related studies on the investigation of extreme market movement days that are: Dennis and Strickland (2002) and Tian *et al.* (2018). However, both these studies use institutional ownership data as a proxy to capture the influence of institutional traders on extreme market movement days. A disadvantage of these ownership data is that they are only available on a quarterly basis, while the extreme market movements are captured on a daily basis. In our view, quarterly data on institutional holdings of each firm's stock is simply too restricted and imprecise to appropriately proxy the influence of institutional traders on extreme market movement days (several of which sometimes occur within a given quarter in Chinese markets). With this in mind, our first contribution is to construct and use a more appropriate proxy for institutional trading behaviour which exploits available daily cash flow data on daily cash flow data on transactions by value and, for each listed firm. Our proxy uses the high value net trades in each company's shares. Our second key contribution is to extend the Dennis and Strickland analysis to take into account the potentially conflating effects of regulator imposed price limits in the Chinese markets. (Such price limits are not in effect in US markets, so were not relevant to Denis and Strickland's study, but their presence in Chinese markets was ignored in Tian *et al.* (op cit.)). Our extension incorporates information on price movements that occur subsequent to days when the price limits are hit, in doing so we draw on a similar set-up used by Chen *et al.* (2019). Our initial empirical findings demonstrate that institutional trading having a destabilizing influence on abnormal stock returns on extreme market movement days, which contrasts with Tian *et al.* (op cit.). This is consistent with our belief that the quarterly proxy used in this prior research does not incorporate the necessary level of detail required to capture the impacts of daily institutional trading behaviour. We went on to add value to the existing literature that ignored the impacts of price limits has been unable to capture important impacts attributable to the interaction of shorter-term institutional trading activity and binding price limits. In particular, we showed that the destabilizing impacts of institutional trading are concentrated in stocks that hit binding price limits on extreme market movement days and in the subsequent behaviour of abnormal returns on these stocks.

In summary, by proposing a more appropriate proxy for institutional investors' daily trading, this chapter contributes to identifying the destabilizing effect of institutional investors on extreme market movement days binded with the price limit effect, which is entirely ignored in the previous research. We hope this chapter provides a better understanding of the source of extreme cases to investors and also implications for the financial regulators regarding the effectiveness of price limit rule imposed.

The third essay (Chapter 4) has identified the source of high volatility in China's stock market and its relation with institutional investors by using a volatility decomposition approach. Given China's stock market has been documented with higher volatility than the other stock markets, it becomes undoubtedly important to understand the patterns of these volatility components, which will also bring insights to investors who seek for portfolio diversification at the international stock markets. In order to identify the sources and drivers of high volatility, particularly idiosyncratic volatility, two prior studies are key: Campbell, Lettau, Malkiel and Xu (hereafter CLMX, 2001), Brandt *et al.*, (2010). Both these studies use a volatility decomposition method proposed by CLMX to investigate the volatility patterns in the U.S. stock market at the level of the market, industry and firm respectively. Although analysis of volatility decomposition within the US stock market is well established, far less attention has been drawn to the Chinese stock market. Our first contribution is to apply the CLMX approach to Chinese daily firm returns data over the period 1998-2018 to decompose total stock return volatility into market, industry and firm components. We find that the market component of total volatility is generally the largest component but firm level (idiosyncratic) volatility is the most volatile. We thereby pay particular attention to idiosyncratic volatility that of the key interests of investors for portfolio diversification. We do not find any trend of idiosyncratic volatility in our investigation period. Instead, idiosyncratic volatility is characterised by an autoregressive process with regime shifts associated with financial crisis periods. Our second contribution is to investigate an unexplored question of whether the trading activity of institutional investors or retail investors is responsible for the time-series behaviour of idiosyncratic volatility in China's stock market. We find idiosyncratic volatility is associated with the trading activity by institutional investors, which contrast the results in U.S. study (Brandt et al., 2010), largely due to the different institutional background. Lastly, we make our third contribution to investigate the idiosyncratic volatility patterns across individual industries. We provide new evidence from industry-level study and show that much of the idiosyncratic volatility is concentrated in China's manufacturing industry, which is a leading indicator of the idiosyncratic volatility in other individual industries. As industry allocation is an increasingly important consideration for active institutional investors (e.g. Cavaglia et al., 2000, Carrieri et al., 2004), our results also contain the implications for investors who consider for home-biased equity allocation policies.

The contribution of Chapter 4 is to provide a comprehensive review of the volatility patterns at market, industry and firm levels by using a volatility decomposition approach. We hope the results contained in Chapter 4 provide implications for investors on portfolio diversification at both international and home-biased level, and for financial regulators to understand better for the underlying risks in China's stock market.

To conclude, this thesis investigated the patterns of high volatility and it's relation with the trading behaviour of institutional investors by using a large dataset constructed by firm-level. Built on the methodology constructed in studies of the Western stock market, this thesis has incorporated the factors unique to China's stock market that are likely to impact the results. As such, the results contained in the thesis are noticeably different from those in studies of the Western stock market. We hope the thesis provides multiple insights to researchers, investors and financial regulators on understanding the patterns of a fast-growing emerging market.

Developments in the openness of China's stock market are continuing at pace. Further analysis of this kind is likely to be helpful in the future, once there is sufficient data to estimate the impacts of new developments. Two potentially interesting issues are likely to be impacts of inclusion of selected shares in the MSCI emerging markets index and progressive moves to increase the weighting attached to these shares toward market value weights; and the financial liberalization in Chinese Star Market. In July of 2019, Shanghai Stock Exchange has launched the Star Market for 25 listed tech companies. The listed stock in this market does not impose price limits on share prices during the first five days of a firm's trading. After these days, they will be subjected to a 20% price limit movement. The investigation of volatility patterns and institutional trading behaviours on this new board leaves for future research.

Appendix

Appendix A. Variables definition

Table A.1: Variables definition

This table presents the definition of variables used in chapter 2. The data of stock price, identity of largest shareholder, analyst coverage, book-to-market ratio, firm size and turnover ratio were obtained from the China Stock Market and Accounting Research (CSMAR) databases. These data with information were supplemented from the Wind Financial Database on institutional ownership.

Variable	Definition
High/Low	The highest/lowest stock price for each listed firm in every trading day.
Volatility Persistence	Volatility persistence estimated from range based autoregressive volatility model of listed firm in every year.
Ownership concentration	The proportion of shares owned by the largest shareholder at the beginning of year
State Owned Enterprise (SOE)	An indicator variable on the nature of the largest shareholder. It equals to one if the largest shareholder of listed firm is government related, and zero if non-government related
of which Central SOE	An indicator variable on the nature of the largest shareholder. It equals to one if the largest shareholder of listed firm is central government related, and zero if not.
Local SOE	An indicator variable on the nature of the largest shareholder. It equals to one if the largest shareholder of listed firm is local government related, and zero if not.
Institutional Ownership	The proportion of shares owned by institutional investors at the beginning of year
of which Active Institutions	The proportion of shares owned by investment funds and foreign investors at the beginning of year.
Passive Institutions	The proportion of shares owned by financial and other institutions at the beginning of year.
Mutual Funds	The proportion of shares owned by investment funds at the beginning of year.
QFII	The proportion of shares owned by foreign investors at the beginning of year.
Financial Institutions	The proportion of shares owned by financial institutions at the beginning of year.
‘Other’ Institutions	The proportion of shares owned by other institutions at the beginning of year.
Analyst coverage	Analyst coverage as the number of analysts who issued forecasts for a firm in a year.
Turnover ratio	Turnover rate computed as the total trading volume of shares divided by the total number of share outstanding at the end of the year.
Firm size	The market capitalization of list firms at the end of year.
Book-to-market ratio	Book-to-market ratio of a firm at the end of year.

Appendix B. Extreme days in Shanghai and Shenzhen Stock Exchange

Table B.1: Extreme days in Shanghai and Shenzhen Stock Exchange

The table reports all extreme days in Shanghai (Shenzhen) stock market when the absolute value of the market return calculated from the relevant composite price index exceeds two standard deviations above mean. Specifically, we report the extreme market movement date, the market return, the numbers of A-shares, regular shares, regular shares that hit the +10% price limit on the extreme day, the numbers of special treatment (ST) shares, of ST shares that hit the +5% price limit and the percentage of all A-shares that hit their upper price limit.

Panel A: Shanghai Up Extreme days

date	market return (%)	no. A-Shares	no. regular shares	no. regular shares that hit +10% price limit	no. of ST shares	no.. ST shares that hit the +5% price limit	% of A- shares that hit the upper price limit
24/05/2010	3.48	832	755	26	77	20	5.5%
21/06/2010	2.90	831	752	4	79	7	1.3%
08/10/2010	3.13	843	767	18	76	6	2.8%
15/10/2010	3.18	835	760	14	75	3	2%
13/12/2010	2.88	844	770	12	74	4	1.9%
25/08/2011	2.92	877	801	8	76	2	1.1%
12/10/2011	3.04	887	808	11	79	4	1.7%
09/01/2012	2.89	891	818	24	73	19	4.8%
17/01/2012	4.18	887	815	53	72	19	8.1%
07/09/2012	3.70	924	885	31	39	1	3.5%
05/12/2012	2.87	921	880	17	41	5	2.4%
14/12/2012	4.32	919	879	23	40	3	2.8%
14/01/2013	3.06	920	881	23	39	4	2.9%
11/07/2013	3.23	907	879	16	28	1	1.9%
09/09/2013	3.39	917	891	23	26	0	2.5%
18/11/2013	2.87	905	877	17	28	1	2%
02/12/2014	3.11	890	870	27	20	1	3.1%
04/12/2014	4.31	889	869	34	20	1	3.9%
08/12/2014	2.81	897	877	52	20	1	5.9%
10/12/2014	2.93	906	885	46	21	2	5.3%
25/12/2014	3.36	908	886	26	22	4	3.3%
05/01/2015	3.58	915	891	51	24	1	5.7%
15/01/2015	3.54	917	893	11	24	0	1.2%
21/01/2015	4.74	919	895	25	24	2	2.9%
27/04/2015	3.04	941	919	52	22	4	6%
11/05/2015	3.04	938	913	79	25	8	9.3%
19/05/2015	3.13	940	918	57	22	9	7%
22/05/2015	2.83	938	917	107	21	11	12.6%
25/05/2015	3.35	934	913	122	21	10	14.1%
01/06/2015	4.71	933	912	159	21	8	17.9%
30/06/2015	5.53	947	925	103	22	0	10.9%
09/07/2015	5.76	661	640	576	21	4	87.7%
10/07/2015	4.54	694	673	587	21	14	86.6%
17/07/2015	3.51	926	905	151	21	8	17.2%
29/07/2015	3.44	941	919	156	22	2	16.8%
04/08/2015	3.69	932	911	204	21	7	22.6%
10/08/2015	4.92	934	911	119	23	7	13.5%

27/08/2015	5.34	907	886	110	21	0	12.1%
28/08/2015	4.82	909	888	218	21	13	25.4%
08/09/2015	2.92	912	890	104	22	7	12.2%
16/09/2015	4.89	920	898	334	22	8	37.2%
08/10/2015	2.97	917	894	47	23	2	5.3%
12/10/2015	3.28	917	894	43	23	3	5%
04/11/2015	4.31	922	900	54	22	3	6.2%
19/01/2016	3.22	998	972	54	26	15	6.9%
29/01/2016	3.09	1006	979	26	27	3	2.9%
16/02/2016	3.29	1003	976	50	27	6	5.6%
02/03/2016	4.26	990	964	72	26	11	8.4%
31/05/2016	3.34	1013	990	24	23	1	2.5%

Panel B: Shanghai Down Extreme days

date	market return (%)	no. A-Shares	no. regular shares	no. regular shares that hit -10% price limit	no. of ST shares	no. ST shares that hit the -5% price limit	% of A-shares that hit the lower price limit
13/01/2010	-3.09	839	769	0	70	3	0.4%
20/01/2010	-2.93	834	767	0	67	12	1.4%
19/04/2010	-4.79	823	752	18	71	40	7%
06/05/2010	-4.11	840	761	7	79	13	2.4%
17/05/2010	-5.07	834	758	97	76	49	17.5%
29/06/2010	-4.27	817	746	28	71	43	8.7%
10/08/2010	-2.89	834	759	1	75	9	1.2%
12/11/2010	-5.16	831	755	66	76	54	14.4%
16/11/2010	-3.98	842	766	15	76	13	3.3%
17/01/2011	-3.03	858	779	7	79	15	2.6%
20/01/2011	-2.92	849	771	2	78	8	1.2%
23/05/2011	-2.93	859	784	6	75	38	5.1%
25/07/2011	-2.96	877	802	5	75	25	3.4%
08/08/2011	-3.79	866	792	20	74	43	7.3%
30/11/2011	-3.27	882	809	4	73	19	2.6%
21/02/2013	-2.97	918	887	0	31	1	0.1%
04/03/2013	-3.65	912	882	37	30	3	4.4%
28/03/2013	-2.82	914	887	3	27	1	0.4%
13/06/2013	-2.83	898	870	5	28	7	1.3%
24/06/2013	-5.30	901	872	69	29	14	9.2%
10/03/2014	-2.86	915	894	6	21	0	0.7%
09/12/2014	-5.43	902	881	61	21	13	8.2%
23/12/2014	-3.03	906	883	12	23	3	1.7%
19/01/2015	-7.7	920	896	99	24	5	11.3%
05/05/2015	-4.06	935	909	12	26	10	2.4%
28/05/2015	-6.5	934	912	225	22	11	25.3%
16/06/2015	-3.47	929	909	27	20	15	4.5%
18/06/2015	-3.67	932	911	33	21	11	4.7%
19/06/2015	-6.42	934	913	381	21	18	42.7%
25/06/2015	-3.46	947	925	28	22	5	3.5%
26/06/2015	-7.40	951	929	736	22	21	79.6%
29/06/2015	-3.34	947	925	471	22	19	51.7%
01/07/2015	-5.23	946	924	318	22	19	35.6%
02/07/2015	-3.48	942	920	526	22	20	58%
03/07/2015	-5.77	933	911	536	22	22	59.8%

08/07/2015	-5.90	710	690	494	20	18	72.1%
15/07/2015	-3.03	928	906	563	22	21	62.9%
27/07/2015	-8.48	939	918	720	21	17	78.5%
18/08/2015	-6.15	928	905	621	23	18	68.9%
20/08/2015	-3.42	930	907	61	23	5	7.1%
21/08/2015	-4.27	931	908	90	23	16	11.4%
24/08/2015	-8.49	924	903	787	21	21	87.4%
25/08/2015	-7.63	918	897	708	21	19	79.2%
15/09/2015	-3.52	921	898	227	23	17	26.5%
21/10/2015	-3.06	899	876	284	23	17	33.5%
27/11/2015	-5.48	950	927	91	23	14	11.1%
04/01/2016	-6.86	983	960	382	23	21	41%
07/01/2016	-7.04	989	964	422	25	22	44.9%
11/01/2016	-5.33	987	962	378	25	24	40.7%
15/01/2016	-3.55	994	968	29	26	3	3.2%
21/01/2016	-3.23	1002	976	35	26	8	4.3%
26/01/2016	-6.42	1001	975	270	26	19	28.9%
28/01/2016	-2.92	1005	979	67	26	9	7.6%
25/02/2016	-6.41	990	964	436	26	21	46.2%
29/02/2016	-2.86	987	961	139	26	21	16.2%
06/05/2016	-2.82	1004	979	9	25	13	2.2%
13/06/2016	-3.21	1019	993	41	26	14	5.4%

Panel C: Shenzhen Up Extreme days

date	market return (%)	no. A-Shares	no. regular shares	no. regular shares that hit +10% price limit	no. of ST shares	no. ST shares that hit the +5% price limit	% of A- shares that hit the upper price limit
24/05/2010	4.28	906	855	33	51	19	5.7%
12/10/2011	3.5	1299	1253	21	46	4	1.9%
09/01/2012	3.72	1336	1295	27	41	14	3.1%
10/01/2012	3.85	1345	1304	40	41	9	3.6%
17/01/2012	5.14	1342	1300	46	42	14	4.5%
07/09/2012	3.75	1471	1427	34	44	2	2.4%
05/12/2012	3.78	1478	1441	26	37	2	1.9%
14/12/2012	4.12	1481	1441	20	40	3	1.6%
14/01/2013	3.63	1471	1431	37	40	2	2.7%
10/12/2014	3.5	1412	1399	68	13	2	5%
20/01/2015	3.39	1402	1389	69	13	3	5.1%
21/04/2015	3.88	1392	1381	112	11	8	8.6%
08/05/2015	4.17	1414	1400	198	14	2	14.1%
11/05/2015	4.48	1421	1407	203	14	4	14.6%
21/05/2015	3.59	1419	1404	276	15	5	19.8%
26/05/2015	3.58	1399	1384	248	15	8	18.3%
01/06/2015	4.79	1385	1371	286	14	4	20.9%
02/06/2015	3.52	1381	1366	297	15	4	21.8%
30/06/2015	4.8	1388	1375	180	13	1	13%
09/07/2015	3.76	678	667	645	11	7	96.2%
10/07/2015	4.09	701	690	660	11	7	95.1%
13/07/2015	4.18	842	831	753	11	7	90.3%
17/07/2015	4.98	1223	1210	356	13	2	29.3%
29/07/2015	4.13	1322	1308	245	14	3	18.8%
04/08/2015	4.77	1333	1319	439	14	6	33.4%

10/08/2015	4.49	1333	1320	183	13	7	14.3%
28/08/2015	5.4	1366	1353	347	13	5	25.8%
08/09/2015	3.83	1386	1372	232	14	1	16.8%
16/09/2015	6.52	1405	1391	728	14	4	52.1%
21/09/2015	3.55	1411	1396	170	15	3	12.3%
08/10/2015	4	1427	1411	138	16	1	9.7%
12/10/2015	4.18	1433	1416	138	17	7	10.1%
22/10/2015	3.71	1435	1420	169	15	2	11.9%
04/11/2015	5.12	1471	1453	144	18	2	9.9%
14/01/2016	3.81	1561	1541	108	20	2	7%
19/01/2016	3.57	1556	1536	91	20	13	6.7%
29/01/2016	3.71	1549	1529	77	20	3	5.2%
02/02/2016	3.42	1550	1530	91	20	7	6.3%
16/02/2016	4.1	1557	1538	124	19	7	8.4%
02/03/2016	4.7	1553	1536	118	17	8	8.1%
14/03/2016	3.56	1553	1537	80	16	5	5.5%
17/03/2016	3.56	1555	1538	76	17	1	5%
18/03/2016	3.65	1553	1536	103	17	1	6.7%
30/03/2016	3.6	1536	1522	82	14	0	5.3%
31/05/2016	4.09	1540	1523	72	17	2	4.8%

Panel D: Shenzhen Down Extreme days

date	market return (%)	no. A-Shares	no. regular shares	no. regular shares that hit -10% price limit	no. of ST shares	no. ST shares that hit the -5% price limit	% of A-shares that hit the lower price limit
Date	Mean Return (%)	Number	Regular	Lower Hit (Regular)	ST	Lower Hit (ST)	Total Lower Hit
20/01/2010	-3.67	814	768	8	46	6	1.7%
19/04/2010	-4.42	879	828	17	51	22	4.4%
06/05/2010	-3.65	891	837	6	54	10	1.8%
17/05/2010	-5.97	888	838	105	50	30	15.2%
18/06/2010	-3.61	929	876	26	53	12	4.1%
29/06/2010	-5.44	934	885	42	49	30	7.7%
12/11/2010	-6.12	1048	1001	78	47	32	10.5%
16/11/2010	-3.49	1051	1002	16	49	9	2.4%
17/01/2011	-4.25	1111	1062	23	49	11	3.1%
20/01/2011	-3.4	1119	1072	1	47	4	0.4%
23/05/2011	-3.63	1192	1143	14	49	30	3.7%
25/07/2011	-3.75	1249	1204	6	45	13	1.5%
08/08/2011	-4.43	1259	1215	46	44	28	5.9%
30/11/2011	-4.01	1315	1275	23	40	19	3.2%
05/01/2012	-3.52	1329	1288	73	41	16	6.7%
13/01/2012	-3.52	1331	1290	34	41	4	2.9%
14/03/2012	-4.09	1370	1332	3	38	21	1.8%
28/03/2012	-4.06	1370	1328	31	42	23	3.9%
16/07/2012	-3.63	1448	1402	83	46	9	6.4%
04/03/2013	-3.54	1482	1430	32	52	13	3%
20/06/2013	-3.39	1461	1436	4	25	3	0.5%
24/06/2013	-6.1	1460	1435	96	25	15	7.6%
08/07/2013	-3.57	1455	1434	18	21	6	1.6%
02/12/2013	-4.96	1431	1409	334	22	14	24.3%
25/02/2014	-3.96	1466	1446	69	20	3	4.9%

10/03/2014	-3.47	1464	1446	37	18	1	2.6%
09/12/2014	-4.31	1410	1397	122	13	6	9.1%
22/12/2014	-3.64	1414	1400	200	14	6	14.6%
19/01/2015	-3.39	1403	1391	36	12	1	2.6%
15/04/2015	-3.68	1383	1372	85	11	3	6.4%
28/05/2015	-5.52	1401	1386	321	15	7	23.4%
16/06/2015	-3.59	1395	1384	101	11	9	7.9%
18/06/2015	-3.57	1390	1377	109	13	5	8.2%
19/06/2015	-5.88	1393	1380	593	13	13	43.5%
25/06/2015	-3.76	1400	1387	106	13	3	7.8%
26/06/2015	-7.87	1409	1396	1232	13	11	88.2%
29/06/2015	-6.05	1401	1388	1024	13	12	73.9%
01/07/2015	-4.79	1396	1383	540	13	11	39.5%
02/07/2015	-5.55	1378	1365	900	13	12	66.2%
03/07/2015	-5.3	1336	1323	818	13	11	62.1%
07/07/2015	-5.34	1135	1122	982	13	12	87.6%
15/07/2015	-4.22	1167	1154	637	13	12	55.6%
27/07/2015	-7	1312	1299	1021	13	11	78.7%
18/08/2015	-6.58	1364	1351	915	13	11	67.9%
21/08/2015	-5.39	1373	1360	248	13	11	18.9%
24/08/2015	-7.7	1376	1363	1304	13	11	95.6%
25/08/2015	-7.09	1379	1366	1166	13	10	85.3%
01/09/2015	-4.61	1377	1363	718	14	9	52.8%
14/09/2015	-6.65	1395	1381	968	14	10	70.1%
15/09/2015	-4.97	1399	1385	466	14	11	34.1%
25/09/2015	-3.44	1414	1398	49	16	2	3.6%
21/10/2015	-5.94	1427	1414	549	13	12	39.3%
27/11/2015	-6.09	1511	1493	210	18	5	14.2%
04/01/2016	-8.22	1563	1545	906	18	16	59%
07/01/2016	-8.24	1564	1546	939	18	16	61.1%
11/01/2016	-6.6	1556	1537	865	19	16	56.6%
13/01/2016	-3.46	1563	1543	129	20	11	9%
15/01/2016	-3.4	1565	1545	53	20	1	3.5%
21/01/2016	-4.01	1556	1536	78	20	6	5.4%
26/01/2016	-7.12	1559	1540	734	19	13	47.9%
28/01/2016	-4.18	1555	1535	180	20	10	12.2%
25/02/2016	-7.34	1549	1533	907	16	12	59.3%
29/02/2016	-5.37	1548	1533	449	15	10	29.7%
20/04/2016	-4.43	1518	1501	58	17	7	4.3%
06/05/2016	-3.65	1541	1519	16	22	8	1.6%
09/05/2016	-3.59	1536	1514	84	22	14	6.4%
13/06/2016	-4.76	1545	1528	189	17	10	12.9%
27/07/2016	-4.45	1605	1583	72	22	7	4.9%
12/12/2016	-4.86	1701	1673	169	28	10	10.5%
16/01/2017	-3.62	1737	1706	57	31	17	4.3%
17/07/2017	-4.28	1810	1792	361	18	9	20.4%

Appendix C. Analysis of Special Treatment (ST) stocks

We firstly outline the methodology employed in the analysis of abnormal returns and abnormal turnover in ST stock, then report on post-extreme day findings for ST stocks.

The regression of ST samples in extreme up days and extreme down days are specified as follows:

$RET_{i,t+n\rightarrow t+m} = \gamma_0 + \gamma_1 UFIVE_{i,t} + \gamma_2 NETBUY_{i,t} + \gamma_3 UFIVE_{i,t} * NETBUY_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} TURNOVER_{i,t} + \gamma_{12} VARIANCE_{i,t} + \gamma_{13} BETA_{i,t} + \varepsilon_{i,t}, n, m \,\epsilon \{1,2,3,4,5,10,20,60,120\}$, (C-1)

$RET_{i,t+n\rightarrow t+m} = \gamma_0 + \gamma_1 LFIVE_{i,t} + \gamma_2 NETBUY_{i,t} + \gamma_3 LFIVE_{i,t} * NETBUY_{i,t} + \gamma_{10} SIZE_{i,t} + \gamma_{11} TURNOVER_{i,t} + \gamma_{12} VARIANCE_{i,t} + \gamma_{13} BETA_{i,t} + \varepsilon_{i,t}, n, m \,\epsilon \{1,2,3,4,5,10,20,60,120\}$, (C-2)

where $RET_{i,t+n\rightarrow t+m}$ is the dependent variable, referring to the market-adjusted abnormal returns on day 1,2,3,4,5 and cumulative abnormal returns over days [6, 10], [11, 20], [21, 60] and [61, 120] for stock i after up extreme day t. $UFIVE_{i,t}$ ($LFIVE_{i,t}$) is dummy variable with the value one if ST stock i hits the upper (lower) price limit of 5% on extreme market movement day t and is zero otherwise. All other variables are defined as in section 3.3.

Our key interest here are the estimated coefficients on the interaction terms involving UFIVE and NETBUY on extreme market up days and involving LFIVE and NETSELL on extreme market down days. More specifically, a positive coefficient of γ_3 in Equation (D-1) (Equation (D-2)) indicates a stronger price delay effect after shares hit the upper price limit (lower price limit) after being subjected to large net buy (net sell) transactions attributable to institutional investors on extreme market up (down) days.

ST stocks

In Appendix C, Panel A and Panel B in Table C.3 (Table C.4) report the regression results of estimating equations (C-1) and (C-2). The Shanghai results again reveal significant positive coefficients on NETBUY for a further two days following extreme market movement days, which indicates that NETBUY has predictive power on returns subsequent returns for ST. The coefficients of interaction term, however, are mostly insignificant.

On extreme down days, the positive coefficient of interaction term LFIVE*NETSELL in the regression for abnormal returns on the first trading day after the extreme movement day suggests that the price reversal effect is stronger for ST stocks that hit the lower price limit after being subjected to large net sell transactions in the Shanghai market. However, we do not find equivalent evidence in the Shenzhen regressions. In summary, the predictive power of net buy or net sell in extreme days on subsequent days is less clear for ST stocks as compared to regular stocks.

Table C.1: Post-extreme day performance of ST stocks in Shanghai stock market

This table records the log abnormal returns and logged abnormal cumulative returns of ST stocks at various horizons subsequent to extreme market movement days. The sample includes all ST stocks listed in Shanghai stock market during 2010 to 2017. Stocks are separated into groups according to the extent of the price rise/fall recorded on the extreme market movement day (day 0). The numbers of shares in each group are reported in column on the far right. CTO refers to the return calculated from the closing price on day 0 to the opening price on day 1. OTC refers to the return calculated from the opening price and the closing price day 1. Day 2, 3, 4 and 5 refer to the abnormal return on the 2nd, 3rd, 4th and 5th relative to day 0. [6, 10], [11, 20], [21, 60] and [61, 120] refer to the cumulative abnormal returns for time windows spanning the 6th to 10th, 11th, to 20th, 21st to 60th, and 61st to 120th day relative to extreme day. Abnormal returns are calculated as each individual stock's daily return minus the expected return derived from market model. The table reports log returns. "***", "**" and "*" represent the significance level at 0.1%, 1% and 5% respectively.

	CTO	OTC	Day 2	Day 3	Day 4	Day 5	[6, 10]	[11, 20]	[21, 60]	[61, 120]	No.
Panel A ST stocks in Shanghai up extreme days											
Upper Hit	0.84%	0.38%*	0.54%**	0.30%	0.02%	0.04%	0.58%	-0.95%	0.80%	0.41%	213
[4%, 5%)	0.03%	0.73%***	0.34%	0.50%*	0.49%*	0.11%	0.39%	1.22%*	0.35%	-0.56%	148
[3%, 4%)	0.04%	0.88%***	0.33%*	0.38%*	-0.08%	0.31%	1.38%**	0.70%	1.34%**	0.54%	176
[2%, 3%)	-0.17%**	0.71%***	0.42%**	0.62%***	-0.14%	0.00%	1.34%*	0.62%	0.56%	1.22%*	240
[-2%, 2%)	-0.11%*	0.09%	0.12%	0.07%	-0.58%***	0.07%	-0.36%	-0.51%	0.60%	0.05%	477
(-5%, -2%)	0.14%	-1.14%*	-0.46%	-1.02%*	-1.51%**	-0.72%	-1.41%	-1.28%	-0.12%	-2.23%	45
Lower Hit	-2.28%***	-0.34%	-2.38%***	-2.06%***	-2.46%***	-0.44%	-1.17%	0.43%	-0.09%	0.56%	31
Panel B ST stocks in Shanghai down extreme days											
Upper Hit	1.68%*	0.10%	0.30%	-0.08%	-1.79%	-0.78%	-0.94%	-0.24%	0.60%	3.1%	26
[2%, 5%)	-0.18%	0.24%	-0.61%	-0.37%	-1.07%*	-0.75%	0.59%	0.80%	-1.01%	0.33%	50
[-2%, 2%)	-0.54%***	0.92%***	-0.07%	0.04%	-0.67%***	-0.38%*	0.79%*	0.39%	0.98%*	0.5%	265
[-3%, -2%)	-0.18%	0.55%**	0.08%	-0.18%	-0.45%*	-0.7%***	0.03%	0.4%	-0.06%	0.94%	159
[-4%, -3%)	-0.51%***	1.03%***	-0.08%	-0.13%	-0.25%	-0.24%	0.91%*	1.31%**	0.94%*	0.29%	179
(-5%, -4%)	-1.06%***	0.37%**	-0.18%	-0.48%***	-0.51%***	-0.19%	-0.42%	0.22%	1.00%*	1.45%**	305
Lower Hit	-2.46%***	0.10%	-0.86%***	-0.81%***	-0.89%***	-0.52%***	-1.17%***	0.24%	-0.06%	0.35%	796

Table C.2: Post-extreme day performance of ST stocks in Shenzhen stock market

This table records the log abnormal returns and logged abnormal cumulative returns of ST stocks at various horizons subsequent to extreme market movement days. The sample includes all ST stocks listed in Shenzhen stock market during 2010 to 2017. Stocks are separated into groups according to the extent of the price rise/fall recorded on the extreme market movement day (day 0). The numbers of shares in each group are reported in column on the far right. CTO refers to the return calculated from the closing price on day 0 to the opening price on day 1. OTC refers to the return calculated from the opening price and the closing price day 1. Day 2, 3, 4 and 5 refer to the abnormal return on the 2nd, 3rd, 4th and 5th relative to day 0. [6, 10], [11, 20], [21, 60] and [61, 120] refer to the cumulative abnormal returns for time windows spanning the 6th to 10th, 11th, to 20th, 21st to 60th, and 61st to 120th day relative to extreme day. Abnormal returns are calculated as each individual stock's daily return minus the expected return derived from market model. The table reports log returns. "***", "**" and "*" represent the significance level at 0.1%, 1% and 5% respectively

	CTO	OTC	Day 2	Day 3	Day 4	Day 5	[6, 10]	[11, 20]	[21, 60]	[61, 120]	No.
Panel A ST stocks in Shenzhen up extreme days											
Upper Hit	1.24%***	0.26%	0.81%***	0.47%*	0.44%	0.59%*	1.08%	0.23%	0.01%	1.62%	148
[4%, 5%)	-0.19%	0.95%***	0.24%	0.28%	0.18%	0.36%	0.69%	1.68%	1.21%	-0.13%	97
[3%, 4%)	-0.24%*	0.63%**	0.17%	0.43%*	0.42%	0.23%	0.77%	1.78%**	1.45%*	0.76%	96
[2%, 3%)	-0.12%	0.62%***	0.29%	0.38%*	0.10%	0.26%	0.57%	0.80%	1.39%*	0.52%	138
[-2%, 2%)	-0.12%	0.58%**	0.54%*	0.03%	0.59%**	0.49%*	1.06%	-1.11%	2.25%**	0.55%	142
(-5%,-2%)	-1.06%	-3.45%**	0.71%	1.30%	-0.05%	0.11%	-5.12%	-5.86%	-0.06%	0.21%	8
Lower Hit	-3.25%*	1.51%	-2.76%	-0.74%	-0.33%	-0.97%	1.76%	0.49%	7.39%	9.39%	8
Panel B ST stocks in Shenzhen down extreme days											
Upper Hit	-0.38%	0.67%	-1.03%	-1.73%	-0.24%	-0.03%	-1.18%	-0.01%	1.79%	-2.2%	17
[4%, 5%)	-1.11%***	0.82%	-1.35%**	-0.85%	-0.91%*	-0.88%*	-3.42%**	-1.43%	0.03%	-0.35%	39
[3%, 4%)	-0.67%***	0.60%**	-0.17%	-0.4%*	-0.34%*	-0.47%**	-0.44%	-0.22%	0.23%	0.93%	170
[2%, 3%)	-0.49%***	0.80%**	0.36%*	-0.09%	-0.12%	-0.12%	-0.08%	0.92%	0.32%	0.95%	105
[-2%, 2%)	-0.54%***	0.62%**	0.37%*	0.02%	-0.11%	-0.25%	-0.03%	0.14%	-0.16%	0.49%	139
(-5%,-2%)	-0.86%***	0.21%	0.08%	0.02%	0.04%	0.04%	0.20%	0.52%	1.22%**	0.77%	254
Lower Hit	-2.23%***	0.07%	-0.52%***	-0.29%**	-0.26%*	-0.02%	-0.09%	-0.06%	0.59%	0.99%**	564

Table C.3: Regression analysis for abnormal returns on ST stocks on the Shanghai Stock Exchange

This table reports the results of estimating equations (D.1) and (D.2) regression to explain abnormal returns of special treatment (ST) stocks estimated on extreme market movement days in the Shanghai stock market over the period 2010 to 2017. Panel A reports the regressions for extreme market up days, in which the key variable UFIVE identifies regular stocks that hit the +5% price limit and NETBUY refers to the large net buy transactions of institutional investors on the extreme market up days. Panel B reports the regressions for extreme down days, in which the key variable LFIVE identifies regular stocks that hit -5% price limit and NETSELL refers to the large net sell transactions attributed to institutional investors on the extreme market down days. Control variables in each regression include SIZE, TURNOVER, VARIANCE and BETA, all variables are as defined in section 3.3. Standard errors are clustered by firm and t-statistics are reported in parentheses. "***", "**" and "*" represent statistical significance at 1%, 5% and 10% levels respectively.

Panel A Abnormal returns on ST stocks following Shanghai extreme market up days

	AR Day1	AR Day2	AR Day3	AR Day4	AR Day5	CAR [6,10]	CAR [11,20]	CAR [21,60]	CAR [61,120]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
UFIVE	0.007	0.005***	0.002	0.006***	0.001	-0.004	-0.006	0.006	0.008
	(1.40)	(2.96)	(0.89)	(2.85)	(0.26)	(-0.95)	(-0.90)	(0.78)	(0.81)
NETBUY	0.607***	0.206	-0.055	-0.336**	-0.676***	0.027	0.164	0.902**	-0.079
	(3.49)	(1.46)	(-0.34)	(-2.42)	(-6.21)	(0.05)	(0.38)	(2.17)	(-0.20)
UFIVE*	0.267	-0.201	0.075	-0.103	0.344	0.976*	-0.682	-0.770	-0.636
NETBUY	(0.68)	(-1.32)	(0.34)	(-0.53)	(1.08)	(1.82)	(-1.01)	(-1.21)	(-0.83)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
constant	0.005	0.068***	-0.005	-0.01	-0.055***	-0.077	0.122**	0.086	0.137**
	(0.21)	(3.21)	(-0.24)	(-0.45)	(-2.82)	(-1.00)	(2.16)	(1.20)	(2.18)
No. Obs.	1330	1330	1330	1330	1329	1328	1326	1313	1286
Adjusted R^2	0.016	0.016	0.026	0.025	0.027	0.004	0.008	0.012	0.004

Panel B Abnormal returns on ST stocks following Shanghai extreme market down days

	AR Day1	AR Day2	AR Day3	AR Day4	AR Day5	CAR [6,10]	CAR [11,20]	CAR [21,60]	CAR [61,120]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LFIVE	-0.023***	-0.006***	-0.005***	-0.002*	0.000	-0.010**	-0.003	-0.008**	-0.005
	(-16.8)	(-5.07)	(-4.67)	(-1.67)	(-0.17)	(-2.53)	(-0.85)	(-2.29)	(-1.46)
NETSELL	-0.331	0.299**	0.360***	-0.267	-0.347***	-0.020	0.561*	0.238	-0.028
	(-1.36)	(2.29)	(2.97)	(-1.37)	(-2.93)	(-0.07)	(1.71)	(0.70)	(-0.08)
LFIVE*	0.701***	0.007	-0.181	0.013	0.137	0.003	-1.701***	-0.175	-0.055
NETSELL	(2.67)	(0.04)	(-1.22)	(0.05)	(0.57)	(0.01)	(-3.57)	(-0.41)	(-0.12)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
constant	0.091***	0.052***	0.036**	0.016	-0.003	0.158***	0.025	0.012	-0.049
	(3.88)	(3.16)	(2.24)	(1.19)	(-0.17)	(2.76)	(0.65)	(0.23)	(-0.76)
No. Obs.	1780	1779	1779	1779	1779	1775	1767	1751	1725
Adjusted. R^2	0.138	0.036	0.017	0.010	0.015	0.021	0.003	0.001	-0.001

Table C.4: Regression analysis for abnormal returns on ST stocks on the Shenzhen Stock Exchange

This table reports the regression evidence of special treatment (ST) stocks estimated from Eq. (B.1) and (B.2) on extreme market movement days in Shenzhen stock market over 2010 to 2017, while samples are further separated into up or down extreme days. Panel A reports the regressions for ST stocks on extreme up days, in which the key variable UFIVE refers to regular stocks hitting 5% price limit and NETBUY refers to the large net buy transactions of institutional investors on the extreme market up days. Panel B reports the regressions for ST stocks on extreme down days, in which the key variable LFIVE refers to regular stocks hitting -5% price limit and NETSELL refers to the large net sell transactions attributed to institutional investors on the extreme market down days. Control variables in each regression include SIZE, TURNOVER, VARIANCE and BETA, all variable are as defined earlier. Standard errors are clustered by firm and t-statistics are reported in parentheses. "***", "**" and "*" represent statistical significance at 1%, 5% and 10% levels respectively.

Panel A Abnormal returns on ST stocks following Shenzhen extreme market up days									
	AR Day1	AR Day2	AR Day3	AR Day4	AR Day5	CAR [6,10]	CAR [11,20]	CAR [21,60]	CAR [61,120]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
UFIVE	0.012***	0.007***	0.005**	0.005**	0.005*	0.004	0.008	-0.011	0.019
	(3.77)	(2.58)	(2.28)	(2.10)	(1.75)	(0.57)	(1.14)	(-1.20)	(1.46)
NETBUY	0.030	-0.160	-0.130	0.208	-0.100	-0.093	1.418**	-1.196***	0.442
	(0.09)	(-0.52)	(-0.89)	(0.97)	(-0.27)	(-0.18)	(2.23)	(-3.68)	(0.94)
UFIVE *	-0.269	-0.157	-0.619***	-0.904***	-0.363	0.770	-2.666**	-0.204	-2.62***
NETBUY	(-0.35)	(-0.29)	(-2.90)	(-4.11)	(-0.54)	(1.11)	(-2.20)	(-0.44)	(-2.88)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
constant	-0.010	0.111***	0.005	-0.004	0.000	0.142**	0.034	0.307***	0.089
	(-0.39)	(6.33)	(0.19)	(-0.15)	(0.00)	(2.25)	(0.34)	(3.25)	(0.87)
Number	637	637	637	637	637	637	636	627	609
Adjusted R^2	0.015	0.028	0.036	0.021	0.002	0.003	0.021	0.021	0.001
Panel B Abnormal returns on ST stocks following Shenzhen extreme market down days									
	AR Day1	AR Day2	AR Day3	AR Day4	AR Day5	CAR [6,10]	CAR [11,20]	CAR [21,60]	CAR [61,120]
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
LFIVE	-0.019***	-0.006***	-0.002	-0.001	0.001	-0.001	-0.002	-0.000	0.002
	(-9.97)	(-4.41)	(-1.18)	(-0.83)	(0.90)	(-0.18)	(-0.56)	(-0.10)	(0.51)
NETSELL	0.245	0.409***	-0.036	-0.438**	0.128	3.198***	0.214	0.418	0.445
	(0.83)	(3.61)	(-0.15)	(-2.56)	(1.03)	(2.79)	(0.61)	(1.01)	(1.16)
LFIVE *	-0.962	0.347	0.840*	0.545	-0.130	-2.899*	0.610	-0.903	-0.516
NETSELL	(-0.69)	(0.84)	(1.95)	(1.56)	(-0.39)	(-1.79)	(0.44)	(-1.05)	(-0.56)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	0.068***	0.043***	-0.006	-0.035*	-0.058***	0.078	0.025	-0.083	0.043
	(3.18)	(3.06)	(-0.354)	(-1.95)	(-3.48)	(1.56)	(0.42)	(-1.38)	(0.67)
No. Obs.	1288	1288	1288	1287	1287	1286	1285	1276	1242
Adjusted R^2	0.114	0.042	0.005	0.006	0.013	0.033	-0.003	-0.003	0.000

Appendix D. Granger causality test among individual industries

Table D.1 shows dynamic patterns of industry-specific volatility (IND) across 15 industries, scientific research and technical service industry is the most important lead indicator of industry-specific volatility as it helps to forecast nearly all of the other industry-specific volatilities (13 of the other 14 industries). Manufacturing and diversified industries are also the important industry-specific lead factor as each of them helps to forecast 8 other industry-specific volatilities. Interestingly, the IND of the construction industry tends to be led by the most of other industry-specific volatilities (8 in 13 other industries).

To summarize, the scientific research and technical service industry appears to be the industry-specific information center as it helps to forecast 12 other industry-specific volatilities and Granger-cased by 7 other INDs. The manufacturing industry also plays a role of important information nexus as it connects to the other 13 industry-specific volatility series.

Table D.1: Dynamics of industry volatility IND cross industries

This table presents Granger-Causality test of dynamic volatility cross industries. An entry marked with symbol * reports the p-values of Granger-Causality test less than 5% significance level, suggesting that series indicated in the row helps to forecast the series indicated in the column. The notations of industry name are same as that in table 4.3.

	A	B	C	D	E	F	G	I	J	K	L	M	N	R	S
A															
B			*		*	*						*	*		*
C	*	*		*	*	*				*		*	*		*
D	*		*		*	*						*	*		*
E															
F	*	*	*	*	*							*	*		*
G															
I															
J							*								
K	*		*		*								*		
L															
M	*	*	*	*	*	*	*	*	*	*	*		*		*
N							*								
R															
S	*	*	*	*	*	*						*	*		

Table D.2: Lags of dynamic IND volatility across industries

This table presents the lag(s) of Granger-causality test of dynamic industry-specific volatility across industries, which are selected from Akaike information criterion (AIC) from multivariate VAR systems, defined as before.

	A	B	C	D	E	F	G	I	J	K	L	M	N	R	S
A		5	5	5	5	5	9	5	5	5	5	5	5	5	5
B	5		12	5	1	6	9	1	1	1	1	14	5	1	6
C	5	12		5	1	2	9	1	1	1	1	10	1	1	5
D	5	5	5		1	5	9	1	2	1	1	10	1	1	5
E	5	1	1	1		1	8	1	1	1	1	2	1	1	1
F	5	6	2	5	1		8	1	1	1	1	10	5	1	11
G	9	9	9	9	8	8		8	8	8	9	10	8	9	9
I	5	1	1	1	1	1	8		1	1	1	2	1	1	1
J	5	1	1	2	1	1	8	1		1	1	2	1	1	1
K	5	1	1	1	1	1	8	1	1		1	2	1	1	1
L	5	1	1	1	1	1	9	1	1	1		2	1	1	1
M	5	14	10	10	2	10	10	2	2	2	2		2	2	10
N	5	5	1	1	1	5	8	1	1	1	1	2		1	5
R	5	1	1	1	1	1	9	1	1	1	1	2	1		1
S	5	6	5	5	1	11	9	1	1	1	1	10	5	1	

Table D.3: Lags of dynamic idiosyncratic volatility across industries

This table presents the lag(s) of Granger-causality test of dynamic firm-specific volatility across industries, which are selected from Akaike information criterion (AIC) from multivariate VAR systems, defined as before.

	A	B	C	D	E	F	G	I	J	K	L	M	N	R	S
A		5	7	13	5	7	9	5	5	5	5	6	5	5	5
B	5		7	5	1	7	10	1	5	1	1	10	5	1	5
C	7	7		1	1	7	8	1	7	1	1	6	7	1	1
D	13	5	1		1	1	8	1	2	2	1	2	1	1	1
E	5	1	1	1		10	10	1	1	1	1	2	1	1	1
F	7	7	7	1	10		9	1	1	1	1	7	7	1	8
G	9	10	8	8	10	9		9	9	9	9	9	9	9	10
I	5	1	1	1	1	1	9		1	1	1	2	1	1	1
J	5	5	7	2	1	1	9	1		1	1	6	1	1	1
K	5	1	1	2	1	1	9	1	1		1	2	1	1	1
L	5	1	1	1	1	1	9	1	1	1		2	1	1	1
M	6	10	6	2	2	7	9	2	6	2	2		5	2	2
N	5	5	7	1	1	7	9	1	1	1	1	5		1	1
R	5	1	1	1	1	1	9	1	1	1	1	2	1		1
S	5	5	1	1	1	8	10	1	1	1	1	2	1	1	

Appendix E. Robustness check

Table E.1: Idiosyncratic volatility and retail trading (2013-2018)

This table reports estimate from monthly Fama-MacBeth cross-sectional regressions over sub-periods over 2013 to 2018. The dependent variables are idiosyncratic volatility estimated from CLMX methodology, CAPM model in equation (4-21), or Fama-French three factors model in equation (4-22). The key independent variable is RTP, referring to the trading volume by retail investors divided by total market volume. Similar to Brandt et al. (2010), we use the cash flow data of the smallest trading group (trading size less than 50,000 RMB) as the proxy for retail trading. All other variables are defined as before.

	Dependent variable:					
	$Log(IV^{CLMX})$		$Log(IV^{CAPM})$		$Log(IV^{FF})$	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(1+INSTITUTION)	0.456***		0.223***		0.266***	
	(13.029)		(13.271)		(16.027)	
Log(1+FUND)		0.780***		0.570***		0.533***
		(9.621)		(13.756)		(11.866)
Log(1+QFII)		0.380		0.142		0.200
		(1.371)		(0.997)		(1.407)
Log(1+FINANCE)		0.312***		0.114***		0.199***
		(4.588)		(3.244)		(5.401)
Log(1+OTHER)		0.423***		0.203***		0.245***
		(12.822)		(12.827)		(15.559)
RTP	-3.739***	-3.740***	-1.936***	-1.934***	-2.117***	-2.115***
	(-35.296)	(-34.890)	(-30.315)	(-29.957)	(-37.361)	(-36.855)
Log(Price)	0.153***	0.131***	0.100***	0.084***	0.100***	0.084***
	(19.386)	(15.981)	(22.114)	(18.400)	(23.944)	(19.381)
Log (lagged IV^{CLMX})	0.229***	0.226***				
	(41.876)	(40.909)				
Log (lagged IV^{CAPM})			0.218***	0.212***		
			(38.659)	(37.451)		
Log (lagged IV^{FF})					0.186***	0.181***
					(32.349)	(31.849)
SIZE	-0.299***	-0.306***	-0.150***	-0.155***	-0.158***	-0.163***
	(-32.619)	(-32.498)	(-30.409)	(-30.582)	(-28.730)	(-28.905)
TURNOVER	0.381***	0.387***	0.209***	0.214***	0.213***	0.218***
	(18.511)	(18.688)	(19.262)	(19.553)	(20.084)	(20.399)
BTM	-0.042***	-0.041***	-0.011***	-0.009***	-0.016***	-0.015***
	(-14.485)	(-13.423)	(-6.210)	(-5.312)	(-9.461)	(-8.531)
ROA	-0.859***	-0.885***	-0.448***	-0.462***	-0.448***	-0.463***
	(-9.497)	(-9.758)	(-9.332)	(-9.567)	(-9.131)	(-9.364)
LEV	-0.016**	-0.015**	-0.025***	-0.024***	-0.014***	-0.014***
	(-2.067)	(-2.032)	(-6.018)	(-6.024)	(-3.368)	(-3.373)

PRETURN	0.056***	0.056***	0.025***	0.025***	0.031***	0.031***
	(3.537)	(3.464)	(2.906)	(2.813)	(3.386)	(3.282)
Constant	3.119***	3.301***	0.273**	0.373***	0.220	0.335**
	(15.746)	(16.249)	(2.405)	(3.207)	(1.640)	(2.427)
Observations	184,572	184,572	184,572	184,572	184,572	184,572
R2	0.601	0.603	0.610	0.613	0.566	0.569
Note:	*p<0.1; **p<0.05; ***p<0.01					

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