The Idiosyncratic Risk in Chinese Stock Market

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Abstract

Using daily stock return data of all listed firms in Chinese stock market from 1998 to 2018, we disaggregate the volatility of common stocks at the market, industry and firm levels. We find market volatility, on average, is the highest while firm volatility tends to lead to market and industry volatility series. None long-term trend time series behaviour exists for all three volatility series and firm volatility is best described by an autoregressive process with regime shifts associated with the structural market reforms or volatile market movements. We further proceed to identify the source of volatility at the industry level and find the idiosyncratic volatility in the largest manufacturing industry not only accounts for the largest proportion in the aggregate firm volatility but also is the lead indicator for the idiosyncratic volatility of other industries. Finally, unlike Brandt *et al.* [*Review of Financial Studies* 23(2): 863-899 (2010)], we find the idiosyncratic volatility in Chinese stock market is associated with high stock trading activities by institutional investors, the result of which is also robust when using other measures of idiosyncratic volatility.

Key words: Volatility decomposition; Regime-switching; Volatility dynamics; Idiosyncratic volatility; Institutional trading behaviour

JEL classification: G11, G12, G14, G18

1. Introduction

Chinese stock market, the largest emerging stock market in the world, 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)[1]. The recent 2015-2016 stock market crash has further attracted the attentions of researchers on the investigation of the volatile feature in Chinese stock markets (Tian et al., 2018; Darby et al., 2019). Understanding the sources and patterns of volatility in Chinese stock market is an undoubtedly important issue for global investors, researchers, regulators and financial analysts as a whole.

In order to identify and study the source of the volatility in U.S. stock market, Campbell, Lettau, Malkiel and Xu (hereafter CLMX, 2001) propose a volatility decomposition approach which disaggregates the volatility of common stocks at the market, industry and firm levels. They find firm volatility[2] is higher than 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. However, Brandt et al. (2010) show that the positive trend of idiosyncratic volatility in U.S. stock market is an episodic phenomenon, which is associated with the trading activities of retail investors. Another related study by Wang (2010) further highlights the importance of CLMXs' contribution on the analysis of stock return volatility at industry level. By using Granger- causality tests, they find the industry of business supplies and the industry of finance are the top two lead indicators of industry-specific volatilities over 1963 to 2008 in U.S. stock market.

The volatility decomposition approach of CLMX enables a clean disaggregation of total return volatility into market, industry and firm levels. Although volatility decomposition in U.S. stock markets has been well established, much less attention has been draw to the Chinese stock market. Following CLMXs' volatility decomposition approach, we address the specific questions as i) what is the key source of high volatility in Chinese stock market? ii) what are the time series behaviours of the volatilities? iii) what is the pattern of volatility across industries? iv) who mainly drives to the firm volatility, institutional or individual investors?

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 at market, industry and firm volatility. We find market volatility, on average, is higher than industry and firm volatilities, though firm volatility tends to be highest in several sub-periods. Unlike the findings from U.S. stock market (CLMX, 2001), we find firm volatility tends to lead the other volatility series. In order to identify the time series behaviour of time series of market, industry and firm volatilities, we first use trend test by Bunzel and Vogelsang (2005) and do not find long-term trend for all volatility series. Given that the results of trend test can be driven by the selection of starting and ending time points (e.g. Bakaert et al., 2012), we thereby fit the Markov regime-switching model with a first-order

[1] Wang et al. (2011) and Li and Giles (2015) show the standard deviation of Chinese stock market index is higher than that of other international stock markets. Rizvi, et al. (2018) show the conditional volatility in Chinese stock market is higher than that of the other emerging stock markets.
[2] We use the terms firm volatility and idiosyncratic volatility interchangeably.

autocorrelation structure (AR (1)) for three volatility series[3]. All the three volatilities are best characterised by an autoregressive with regime shifts, and the shifts of market and industry volatilities to high variance regime are mostly related to financial market crisis periods. Firm volatility, however, exhibits less stable feature compared to market industry volatilities, and shifts to high variance regime more frequently.

To understand well the frequent risen and fallen feature of firm volatility, we further investigate the firm-specific volatility patterns in individual industries. 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 firm volatility is not due to the trade-off effect of mixed upward and downward trend across industries. We then find the firm-specific volatility is particularly high in the manufacturing industry, the largest industry in Chinese stock market which accounts for the average weight of 0.393 in total market value. Furthermore, multivariate Granger-causality test suggests the firm-specific volatility in manufacturing industry is also the lead indicator to the idiosyncratic volatility in other industries.

Finally, we investigate whether the risen or fallen of the idiosyncratic volatility is associated to the trading activities of institutional or retail investors. Despite Nartea et al. (2013) conjecture (do not test) 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 the destabilizing behaviours of large or institutional investors in 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 the idiosyncratic volatility is significantly associated with large stock price and trading activities of institutional investors. Our results contrast the findings of Brandt et al. (2010) for U.S. stock market. Our results are also robust when using other measures of idiosyncratic volatility such as CAPM and Fama-French three factors model.

This paper contributes to the literature in the following three aspects. First, to the best of our knowledge, this is the first paper decomposing the volatility common stocks into market, industry and firm levels to identify the source of high volatility in Chinese stock market. We find that market volatility is, on average, highest while firm volatility tends to be the lead indicator in Chinese stock market and is less stable than other two volatilities.

Second, we are the first to provide volatility patterns in individual industries. We present the evidence that idiosyncratic volatility in the manufacturing industry not only accounts for largest proportion in aggregate firm volatility, but also helps to forecast the firm volatility in other industries. Regarding the

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

industry-specific volatility, however, scientific research and technical service industry tends to be the lead indicators to the other industries.

Third, we contribute to a number of recent studies on idiosyncratic volatility in Chinese stock market (e.g. Wan, 2018; Gu et al., 2018; Xie et al., 2019; Gu et al., 2019). We show the idiosyncratic volatility in Chinese stock market is associated with high stock price and driven by institutional investors, which contrasts the findings in U.S. stock market (Brandt et al., 2010) and the conjecture by Nartea et al. (2013).

The rest of the paper is organized as follows. In section 2, we introduce the data used, the methodology of volatility decomposition and present results of decomposition. The time series behaviours of three decomposed volatility components have been reported in section 3. Section 4 further investigates the sources and patterns of volatility within individual industries, followed by cross regressions testing the key determinants of idiosyncratic volatility in Chinese stock markets in section 5. Finally Section 6 concludes. The results of dynamic pattern of industry-specific volatility in individual industries can be accessed by Appendix A. The robustness check results of retail trading can be accessed by Appendix B.

2. Volatility decomposition

2.1 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 the sample are 804 in the year of 1998, 1664 in year 2009, and finally increase to 3568 in the end of study periods of 2018.

2.2 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 return 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:

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

Computing the variance of the industry return yields:

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

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

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

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

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

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

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

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:

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

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

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

The variance of firm return is represented as:

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

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

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

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

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

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

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

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:

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

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

$$\sum_i w_{it} \sum_{j\epsilon i} w_{jit}\,Var\,(R_{jit}) = \sum_i w_{it}\,R_{it} + \sum_i w_{it} \sum_{j\epsilon i} w_{jit}\,Var\,(\varphi_{jit})$$

$$= Var\,(R_{mt}) + \sum_i w_{it}\,Var\,(\varepsilon_{it}) + \sum_i w_{it}\sigma^2_{\varphi it}$$

$$= \sigma^2_{mt} + \sigma^2_{\varepsilon t} + \sigma^2_{\varphi t}, \quad (13)$$

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.

2.3 Estimation

Following 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 firm volatility (FIRM) respectively. The sample volatility of market return in month t, represented as MKT_t, is computed as:

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

where μ_m is defined as the mean of market return R_{ms} in month t; s denote the day 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 residual in equation (), and then the average industry capitalization weighted volatility is expressed as:

$$IND_t = \sum_i w_{it} \sum_{s\epsilon t} \epsilon^2_{is}. \quad (15)$$

where ϵ^2_{is} 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 firm volatility is conducted in the similar way. We first sum the squares of the firm-specific residual in equation () in month t for each firm, and then compute the weighted average firm volatility in each industry. Finally, we average over firm volatility in all industries to obtain the average firm volatility FIRM_t in month t as

$$FIRM_t = \sum_i w_{it} \sum_{j\epsilon i} w_{jit} \sum_{s\epsilon t} \varphi^2_{jis}. \quad (16)$$

where φ^2_{jis} 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.

Figure 1, 2 and 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 lag of 12.

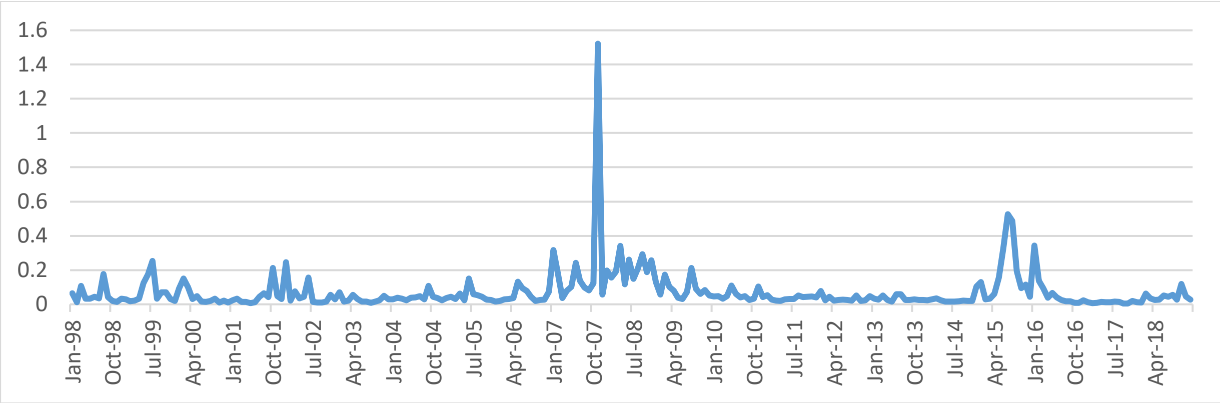
Market volatility shows its well-known patterns as various paper reported regarding index return volatility in Chinese stock markets. In comparison with Panel A and Panel B in Figure 1, market volatility is relatively stable and has a slow-moving component with high-frequency noise. A notable evidence of market volatility is that it is particular high around 2008 and 2015, which reveals the fact that the stock market crash in year 2007-2008 and 2015-2016 led to enormous increase in market volatility. Figure 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 and particularly high around 2008 and 2015.

Figure 3 presents the firm volatility FIRM from 1998 to 2018. Looking at both Panel A and Panel B for firm 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 firm volatility, firm volatility is also particularly high around year 2005 and year 2013. Different from MKT and IND in which the volatility in market crash of year 2007-2008 are much higher than that of year 2015-2016, the spikes in FIRM show its higher increase in the recent market crash of year 2015-2016 rather than that of 2007-2008. This indicates that firm 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 firm volatility FIRM, however, is more unstable with a larger amount of high-frequency noise and more spikes apart from market crash period.

Figure 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)

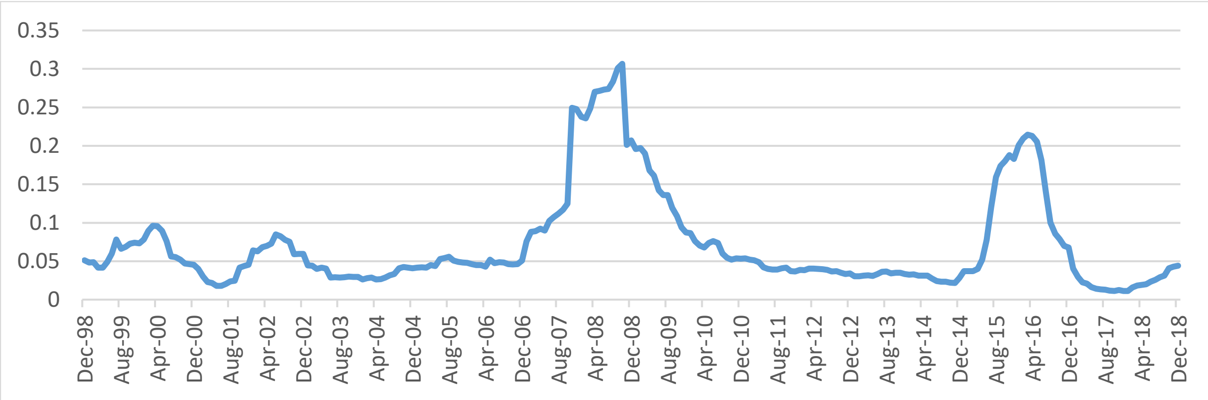
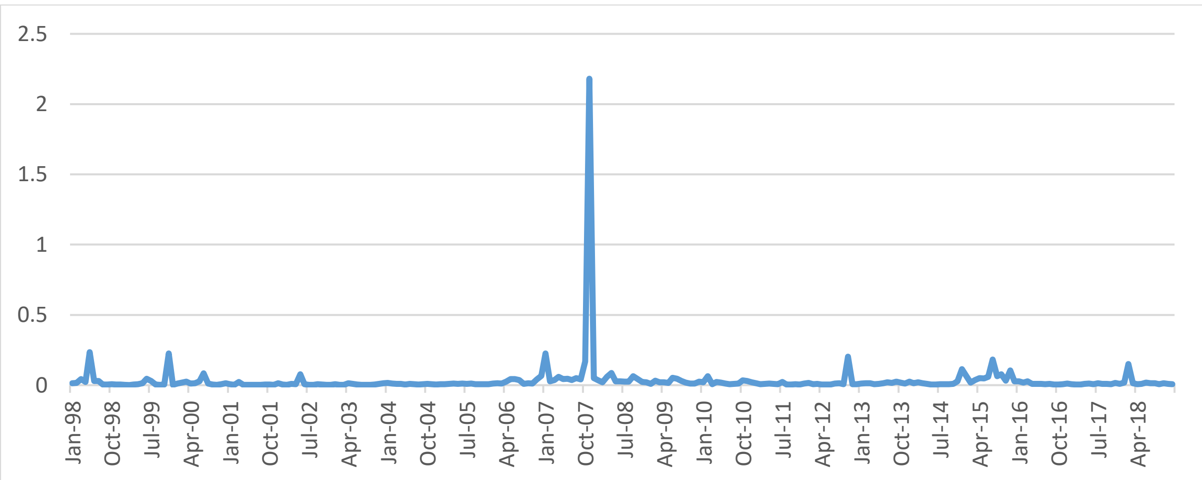


Figure 2. Annualized industry-level volatility IND. The upper chart shows the annualized variance within each month of daily industry returns relative to market over 1998 to 2018. The lower chart shows a backwards 12-month moving average of IND.

Panel A. Industry volatility



Panel B. Industry volatility, MA (12)

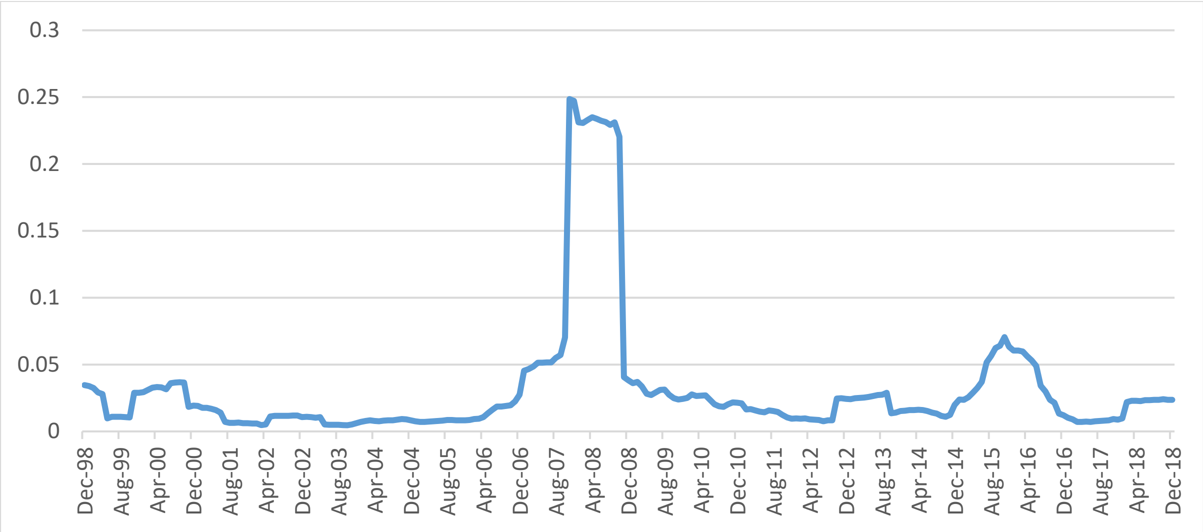
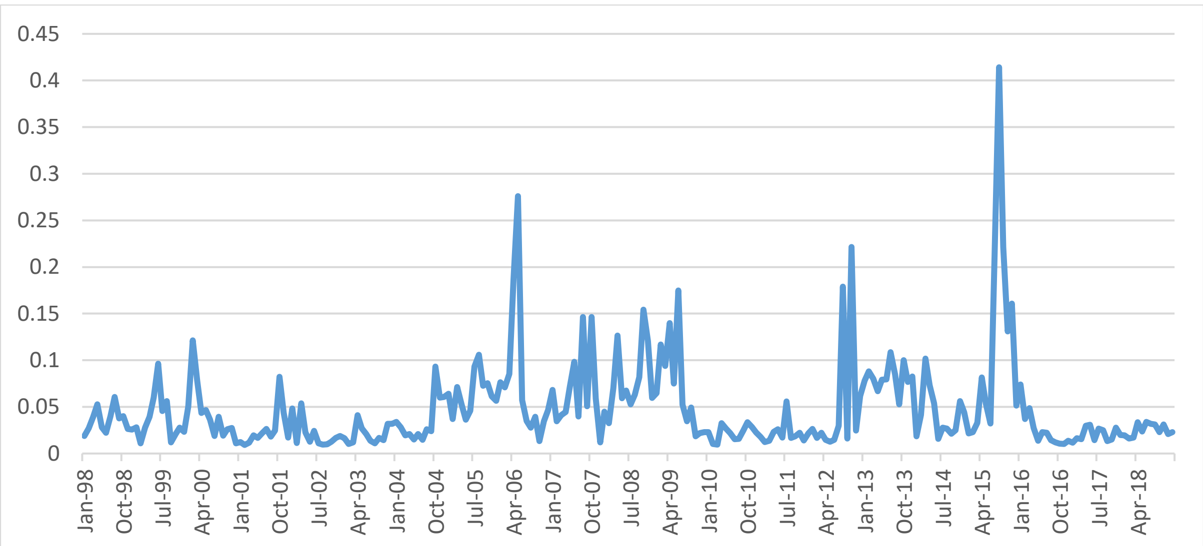


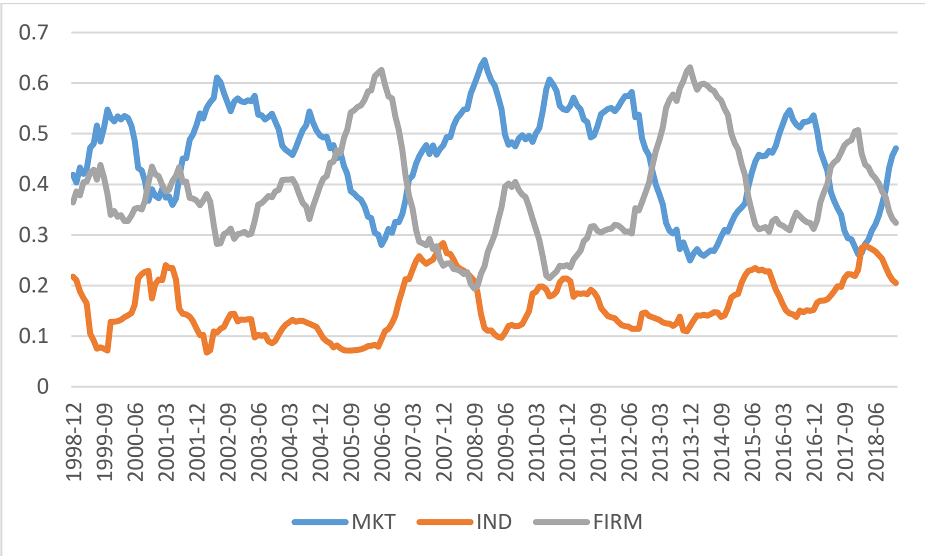
Figure 3. Annualized firm-level volatility FIRM. The upper chart shows the annualized variance within each month of daily firm returns relative to the firm's industry over 1998 to 2018. The lower chart shows a backwards 12-month moving average of FIRM.

Panel A. Firm volatility



Panel B. Firm volatility, MA (12)

Figure 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.



In order to identity the weights of the three volatility components in each month over the sample period, we further plot the three components together with backwards 12-month moving average processes based on the corresponding weights, as shown in figure 4. Consistent with the findings in figure 1-3, the weight of IND is lower than MKT and FIRM in most of the observation periods. In comparison between market and firm 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 market crash period. A plausible explanation is that financial markets' volatility increases substantially and move together during crisis[4], leading to the less amount of increased spike of FIRM than that of MKT. Firm volatility, however, is higher than market volatility in mainly three periods which are around 2006, 2014 and 2017. From next chapter, we proceed to investigate the time series behaviour of the three volatility series so as to identify the determinants of the risen or fallen evidence of volatility series.

3. Time series behaviour of volatility components

3.1 Descriptive statistics

Panel A of Table 1 presents the descriptive statistics of the monthly annualized volatility series of MKT, IND and FIRM, estimated from CLMX methodology. Consistent with Figure 1-3, 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 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 is presented in panel D. The results reject the presence of a unit roots for all three volatility components at 1% level[5].

In order to formally test the trends of volatility series, we follow CLMX and use Bunzel and Vogelsang (2005) linear time trend test[6]. The benchmark model is

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

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 null hypothesis of $b_1 = 0$, in which the suffix "Dan" denotes the use of "Daniel Kernel" to nonparametrically 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 1 shows the results of t-DAN trend test, and we can not reject the null hypothesis that there is no trend observed for the all three volatility measures (MKT, IND and FIRM). The evidence of no long-term trend in the time series behavior of idiosyncratic volatility is supportive to findings of

[4] See among others, Braun et al., 1995, Cappiello et al., 2003, Kotkatvuori-Ornberg et al., 2013.
[5] 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.
[6] 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).

Nartea et al. (2013) using Fama-French three factors model to measure aggregate idiosyncratic volatility.

Table 1. Descriptive statistics

This table presents the descriptive statistics and trend test of monthly volatility components of annualized (×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 regressions with a constant, and regressions with a constant and a trend. Finally, Following CLMX and Bunzel and Vogelsang (2005), we tests 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 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
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

3.2 Granger Causality

Next, we are interest in whether the three volatility components help to forecast each other. Table 2 investigate the 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 VARs including all three volatility components series. The lag length of VARs is selected from Akaike information criterion. In bivariate system, FIRM tend to Granger-cause both MKT and IND whereas IND tend 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 VARs as Panel B shows. IND fails to predict MKT in trivariate case. Further, both MKT and IND tend to Granger-case FIRM in trivariate VARs. Different from CLMX (2001) who reports that MKT tends to lead the other volatility series in U.S. stock market, our finding suggests that FIRM is helpful to forecast the other volatility components.

Table 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 result in bivariate VAR system for each pair while Panel B reports the result in 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 equation, 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)

3.3 Regimes switching

A number of studies point out that the results of trend test can be influenced by the selection of starting and ending time points (e.g. Bakaert et al., 2012; Nartea et al., 2013). Bakaert et al. (2012) investigate the aggregate idiosyncratic volatility in 23 developed markets and do not find the evidence of upward trends after extending the samples to 2008. Importantly, they suggests 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 another words, if the test period starts from low volatility point and ends with high volatility point, it is easily to identify the positive trend in 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.

Nartea et al. (2013) investigate the time behaviour of monthly aggregate idiosyncratic volatility, constructed from Fama-French (1993) model, in Chinese stock market from 1994 to 2011, and do not find the long-term trend of idiosyncratic volatility. Instead, the idiosyncratic volatility is also best described by autoregressive process with regime shifts, and further coincide with structural market reforms.

Similar to Bakaert et al. (2012), Nartea et al. (2013) and Garcia et al. (2014), we fit the Markov regime-switching model with a first-order autocorrelation structure (AR (1)) for three volatility components, and particularly interested in the idiosyncratic volatility. 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:

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

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 $\mathrm{i,j} \in \{1,2\}$:

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

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

Table 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 regime displays a higher probability of remaining in the same state. The regime 2 also has higher volatility than regime 1 for all MKT, IND and FIRM volatility. Thus consistent with findings of Bekaert et al. (2012) and Nartea et al. (2013), we find the idiosyncratic volatility in Chinese stock market can be characterized by a stationary autoregressive process that occasionally switches between high and low volatility regimes, and the similar patterns also appears for market and industry volatility.

Table 3 Regimes switching model

This table reports the parameter estimates of regime-switching model specified from equation (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 5 shows the smoothed probabilities of being in high-variance regime (regime 2) for time series of all three components over 1998 to 2018. Panel A shows that the market volatility was in low volatility regime for the majority of study period except for two evident high volatility regimes periods of market crashes around 2007-2008 and 2015-2016. The industry volatility in Panel B shows the similar pattern whereas appearing to be more stable in low volatility regime compared to market volatility.

We are particularly interested in the firm volatility series as presented in Panel C of Figure 5. Similar to market and industry volatility, firm volatility was also in high volatility regime during market crashes periods. However, firm volatility shifts more frequently between high and low volatility regimes than market and industry volatilities in other study periods. Similar to Nartea et al. (2013), we find firm volatility tends to stay in high volatility regime over the majority of periods before market liberalization, allowing domestic investors to purchase B shares, in the end of 2000. Afterwards, the firm 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 the one-year high volatility regime duration may be related to the market index hitting the peak in the June of 2001 and afterwards keeping a decreasing tendency until the early 2002. Since the Nov 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[7], suggesting the reform of split-share structure led to a consequence increase in the volatility of idiosyncratic volatility. The idiosyncratic volatility shifts back to low volatility regime since the end of 2009 after the financial crisis period 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 in the middle of 2016 when the stock market crash of 2015-2016 comes to an end. The shifts to high variance regime around 2013 may be related to the 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

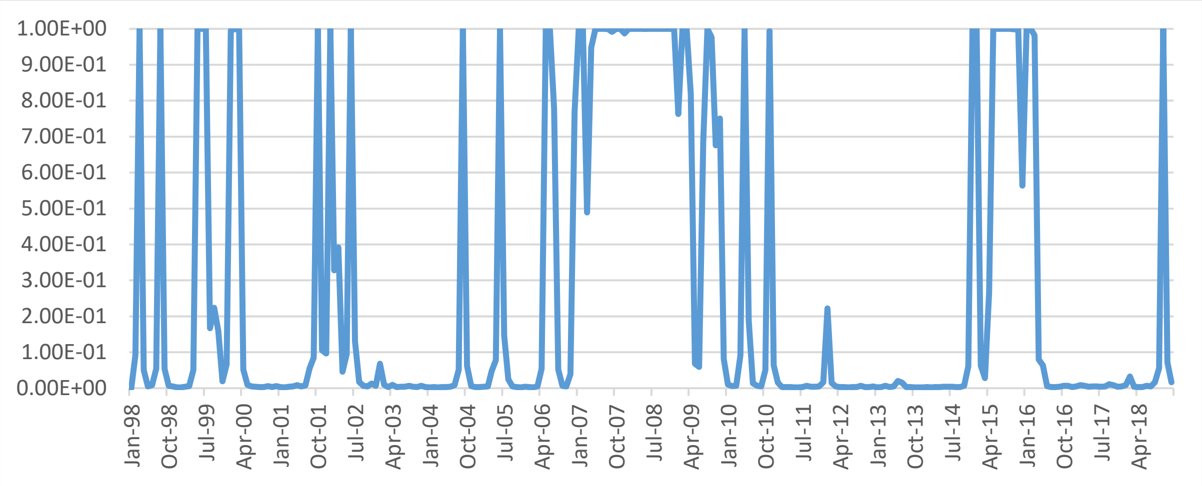
[7] China Securities Regulatory Commission announced '*Circular of China Securities Regulatory Commission on Distributing the Measures for the Administration of the Share-trading Reform of Listed Companies'* at Sep 4, 2005, which denotes the implementation of split-share reform in Chinese stock market.

liberalization (e.g. Shanghai-Hong Kong Stock Connect, Shenzhen-Hong Kong Stock Connect and inclusion of MSCI Emerging Markets Index[8]).

In sum, results from Table 3 and Figure 5 are consistent with the trend test findings that all the three volatility series shows no long-term trend. Instead, the volatility series are characterized by an autoregressive process with regimes shifts. Further, the shifts of high volatility regime of market and industry volatilities are mainly related to financial crisis periods. The regime shifts of firm volatility, however, not only related to financial crash but also coincide with structural market reforms and the movement of market index.

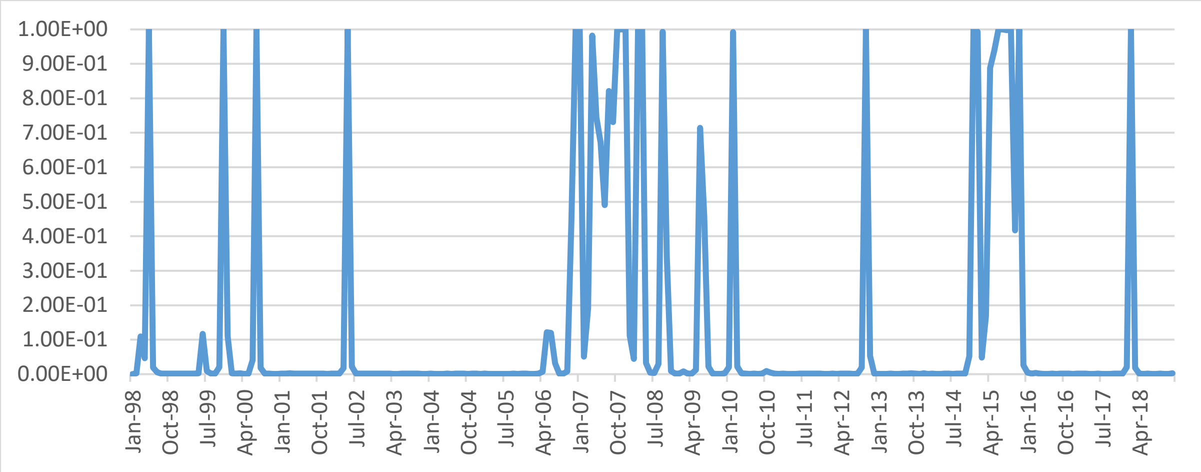
Figure 5. Regime probabilities for MKT, IND and FIRM The regime probabilities of market, industry and firm volatilities are estimated from equation (17).

Panel A. Market volatility

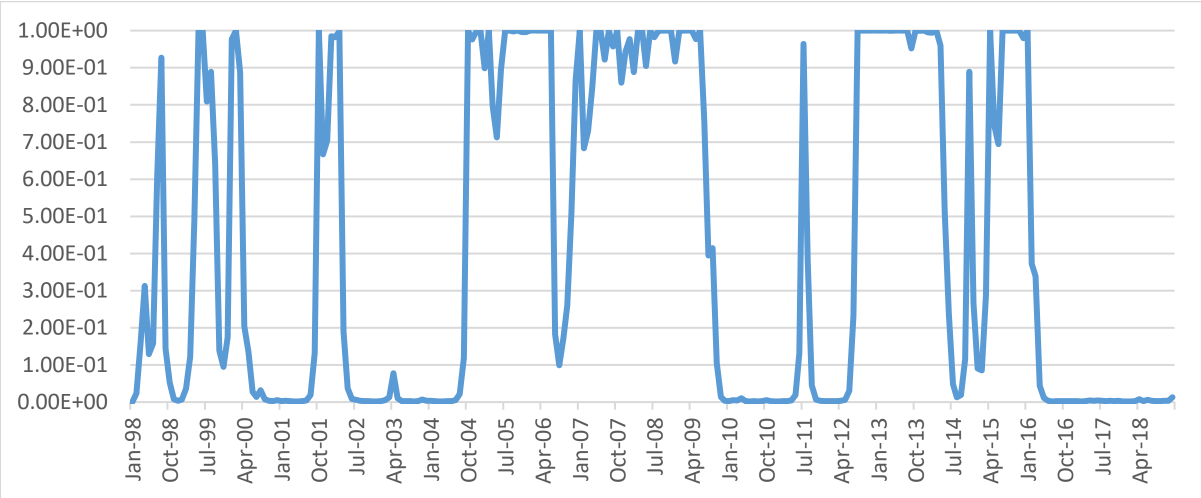


Panel B. Industry volatility

[8] 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.



Panel C. Firm volatility



4. 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 industry- or firm-specific volatility difference across industries. In this section, in order to further identify the source of high volatility in Chinese stock market, 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) argue 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 analysis of volatility patterns at industry level 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 so as to identify the most important lead indicators of industry- or firm-specific volatilities. As presented from the earlier sections, the firm volatility not only plays more important role but also tend 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 A.

4.1 Individual industries

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

$$R_{it} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it}. \tag{19}$$

The volatility of industry return is thereby:

$$Var(R_{it}) = \beta_{im}^2 Var(R_{mt}) + \tilde{\sigma}_{it}^2, \tag{20}$$

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:

$$R_{jit} = \beta_{im} R_{mt} + \tilde{\varepsilon}_{it} + \varphi_{jit}, \tag{21}$$

The weighted average firm volatility in an industry is thereby:

$$\sum_{j \in i} w_{jit} Var(R_{jit}) = \beta_{im}^2 Var(R_{mt}) + \tilde{\sigma}_{it}^2 + \sigma_{\varphi it}^2, \tag{22}$$

where $\sigma_{\varphi it}^2$ is defined as before. The residuals of $\tilde{\varepsilon}_{it}$ in equation (18) and φ_{jit} in equation (20) are used to construct industry-specific and firm-specific volatility for individual industries.

Table 3 shows the manufacturing industry is the largest industry in our sample with an average weight of 39.3 percentage of the total market capitalization over the full sample, followed by the financial industry accounting for 21 percentage of the total market capitalization. The industry betas of most industries listed in Table 3 is around to unity, and the beta is highest for mining industry whereas lowest for financial industry.

Panel A and Panel B of Table 3 display the industry and firm-level volatility cross 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 of aggregate FIRM. 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, suggesting the aggregated 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.

Previously we documented that there is no trends for both IND and FIRM on average for aggregated data. Now we 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. 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 3 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 linear trends of aggregate IND and FIRM are due to the non-existing trend in each industry rather than the trade-off effect across industries.

Table 3 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 less than ten firms in each industry. The industry volatility IND and firm volatility FIRM has been annualized and been multiplied by 100 for convenience. 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.

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

4.2 Dynamic patterns of volatility across industries

4.2.1 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. The lag order 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 the two testing volatility series of y_{1t} and y_{2t}, market volatility of y_{3t} and a weighted average volatility series of y_{4t} from other industries. If the series is stationary, the vector process Y_t can be modelled as the following autoregressive process with p lag(s):

$$Y_t = \alpha + \sum_{l=1}^{p} \Gamma_l \, Y_{t-l} + \mu_t, \text{ t=1, 2, 3..., T,} \tag{23}$$

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 :

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

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

4.2.2 Findings

The results of multivariate Grange-Causality test FIRM, as our key interest, across industries are presented in Table 4 and the results related IND can be accessed in Table A-1 of Appendix. The lag (s) selected from AIC in multivariate VAR systems can also be accessed in Table A-2 and Table A-3 in Appendix for industry-specific and firm-specific volatility respectively.

The Granger-Causality test suggests that the FIRM in manufacturing industry tend to lead most of the other firm-specific volatilities (11 of the other 13 industries). The FIRM in wholesale and retail industry is also the 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 the idiosyncratic volatility in other industries.

Table 4 Dynamics of firm 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 name are same as that in table 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	*		*	*		*	*	*		*			*

5. Determinants of idiosyncratic volatility

We have documented that idiosyncratic volatility of stock returns in Chinese stock markets are best characterized by an autoregressive process with regime shifts. Further, compared to market and industry volatility, idiosyncratic volatility is more active in switching between high and low variance regimes. It is nature 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.

5.1 Hypotheses development

The proposed explanation 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).

Within 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 increase and subsequent reversal phenomenon of idiosyncratic volatility is at least partially associated with retail investors. Nartea et al. (2013) investigate the time series behaviour of idiosyncratic volatility and find 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, 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 via buying on the day when a stock hits the 10% upper price limit and then sell on the next day. Darby et al. (2019) use cash flow data of 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 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, the stocks of which are held by proportionally more by retail investors than institutional investors. This is because institutional investors tend to hold large-price stocks for not only prudence reasons but also the less per share trading costs compared to actively trades on large positons 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 2. Idiosyncratic volatility of stock return is positively associated with stock price in Chinese stock markets.

5.2 Model specification

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

$$IV_{it}^{CLMX} = \sum_{s\epsilon t} \epsilon_{is}^{2}, \tag{24}$$

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 perspective 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 1 and Hypothesis 2 by specifying the following model using Fama and MacBeth (1973) estimation:

$$\mathrm{Log}(\mathrm{IV}_{i,t}) = \alpha + \beta_1 Log(1 + INSTITUTION_{i,t}) + \beta_2 ITP_{i,t} + \beta_3 \mathrm{Log}(\mathrm{PRICE}_{i,t}) + \beta_4 \mathrm{Log}(\mathrm{IV}_{i,t-1}) + \beta_5 SIZE_{i,t} + \beta_6 TURNOVER_{i,t} + \beta_7 BTM_{i,t} + \beta_8 ROA_{i,t} + \beta_9 LEV_{i,t} + \beta_{10} PRETURN_{i,t} + \varepsilon_{i,t}, \tag{25}$$

where $\text{Log}(\text{IV}_{i,t})$ is the dependent variable, referring to the natural log 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 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 1, and the positive coefficient of β_3 translates Hypothesis 2; the other control variables included are lagged idiosyncratic volatility ($\text{Log}(\text{IV}_{i,t-1})$), 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.

The control variables included for the reasons as follows. One-month lag return volatility included is to control for auto-correlation effect of the volatility persistence. The inclusion of size is to ensure the relationship between idiosyncratic volatility and institutional ownership or trading is not driven by size. This is due to i) institutional investors prefer to invest in large firms (e.g. Lakonishok et al., 1992); and ii) firm size is documented as the risk factor (Banz, 1981; Fama and French, 1993). 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 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 know effects of past returns on trading behaviour of investors (e.g. Barber and Odean, 2008) such as herd behaviour, contrarian strategy and exhibition of disposition effect.

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 6). 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 high 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 5. 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 measure by CLMX methodology, firm size, stock price, percentage of shares owned by institutional investors, turnover ratio measure 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 6 shows the findings in the multivariate framework using Fama-MacBeth monthly cross-sectional regressions. Column 1 to 4 include the full samples without institutional trading variable 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 1) is our key interest in this section and we use the 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 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 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 largest 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 relation 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. To summarize, our results are supportive to Hypothesis 1 that institutional investors drive to the idiosyncratic volatility of stock returns in Chinese stock market.

Table 6 also reports the coefficients of stock price which is our key interest of Hypothesis 2. We find the coefficients of stock price are all positive and significant at 1% significance level, which is consistent with Hypothesis 2 that the high idiosyncratic volatility is associated with large 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 is 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, given the stock price consistent. Likewise, stocks with higher volume turnover tend to have 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 attracts more speculative exuberance and thereby having higher idiosyncratic volatility. Furthermore, as expected, companies with high idiosyncratic volatility is associated with lower return on asset and high 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. Finally, we find the idiosyncratic volatility is positively associated with past returns, particularly in the analysis of 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.

Table 6 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 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 measure as the 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					

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:

$$R_{jt} = \alpha_{jt} + \beta_{mt} R_{mt} + \mu_{jt}^{CAPM}, \tag{26}$$

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:

$$R_{jt} = \alpha_{jt} + \beta_{1t} MKT_t + \beta_{2t} SMB_t + \beta_{3t} HML_t + \mu_{jt}^{FF}, \tag{27}$$

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 7 shows the robust 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 6 in which idiosyncratic volatility is estimated from CLMX approach, the results in robustness are both quantitatively and qualitatively similar. In sum, our study provide strong evidence that institutional investors drive to the idiosyncratic volatility in Chinese stock market, the results of which are also robust using 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. Likewise, retail trading proportion is construct by the retail trading volume divided by total market volume. We find the coefficients of RTP are significantly negative in all regressions, indicating the trading activities by retail investors reduces the idiosyncratic volatility in

Chinese stock market. All the other findings are quantitatively and qualitatively similar. The results can be accessed in Appendix B.

Table 7 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 (26) or Fama-French three factors model in equation (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

6. Conclusion

Utilizing the daily data of the universe of all traded Shanghai and Shenzhen Stock Exchanges firms from 1998 to 2018, we investigate the sources and patterns of volatility in Chinese stock market by decomposing the volatility of common stocks at market, industry and firm levels. We show market volatility, on average, is highest among three volatilities. More importantly, firm volatility tends to lead market and industry volatilities. We then conduct a trend test showing no evidence of long-term trend of all three volatilities. By fitting the Markov regime switching model, we show firm volatility is less stable compared to other volatilities and switches more frequently between the high and low variance regimes.

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

Finally, we identify key determinants of the idiosyncratic volatility in Chinese stock market by employing Fama-MacBeth cross sectional regression. We show that idiosyncratic volatility is positively and significantly associated with stock price, institutional ownership and proportion of institutional trading, the results of which are robust for the other classic measures of idiosyncratic volatility. Moreover, investors' trading behaviour plays a key role in determining the idiosyncratic risk in Chinese stock markets, which is different from the retail trading effect in the U.S. stock market.

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Reference

Bai, J., Perron, P., 1998. Testing for and Estimation of Multiple Structural Changes. *Econometrica*, 66, 47–79.

Barber, B. M., Odean, T., 2008. All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors. *Review of Financial Studies*, 21, 785–818.

Barber, B. M.,Odean, T., Zhu, N., 2009. Do Retail Trades Move Markets? *Review of Financial Studies*, 22,151–186.

Banz, R., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), 3-18.

Brandt, M.W., Brav, A., Graham, J., Kumar, A., 2010. The idiosyncratic volatility puzzle: time trend or speculative episodes? *Review of Financial Studies*, 23 (2), 863–899.

Braun, P., Nelson, D., Sunier, A., 1995. Good news, bad news, volatility, and betas. *Journal of Finance*, 50, 1575–1603.

Bunzel, H., Vogelsang, T.J., 2005. Powerful trend function tests that are robust to strong serial correlation, with an application to the Prebisch–Singer hypothesis. *Journal of Business and Economic Statistics*, 23, 381–394.

Bekaert, G., Hodrick, R., Zhang, X., 2012. Aggregate idiosyncratic volatility. *Journal of Financial and Quantitative Analysis*, 47 (6), 1155–1185.

Bennett, J. A., Sias, R. W., Starks L. T., 2003. Greener Pastures and the Impact of Dynamic Institutional Preferences. *Review of Financial Studies*, 16 (4), 1203–1238.

Boehmer, E., Kelley, E.K., 2009. Institutional investors and the informational efficiency of prices, *Review of Financial Studies*, 22(9), 3563–3594.

Campbell J. Y., Ramadorai T., Schwartz A., 2009. Caught on Tape: Institutional Trading, Stock Returns and Earnings Announcements, *Journal of Financial Economics*, 92 (1), 66-91.

Campbell, J.Y., Lettau, M., Malkiel, B.G., Xu, Y., 2001. Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk. *Journal of Finance*, 56, 1–43.

Cappiello, L., Engle, R.F., Sheppard, K., 2006. Asymmetric Dynamics in the Correlations of Global Equity and Bond Returns. *Journal of Financial Econometrics*, 4 (4), 537–572.

Che, L., 2018. Investor types and stock return volatility. *Journal of Empirical Finance*, 47, 139-161.

Chen, T., Gao, Z., He, J., Jiang, W., Xiong, W., 2019. Daily price limits and destructive market behavior, *Journal of Econometrics*, 208 (1), 249-264.

Darby, J., Zhang, H., Zhang, J., Institutional Trading in Volatile Markets: The Case of Chinese Stock Markets (April 26, 2019). Available at SSRN: https://ssrn.com/abstract=3378571 or http://dx.doi.org/10.2139/ssrn.3378571

Li, Y., Giles, D.E., 2015. Modelling Volatility Spillover Effects Between Developed Stock Markets and Asian Emerging Stock Markets. *International Review of Economics & Finance*, 20 (2), 155-177.

Ferreira, M.A., Gama, P.M., 2005. Have world, country and industry risks changed over time? An investigation of the developed stock markets volatility. *Journal of Financial and Quantitative Analysis*, 40, 195–222.

Foucault, T., Sraer, D., Thesmar, D., 2011. Individual investors and volatility. *Journal of Finance*, 66, 1369–1406.

Fama, E., French, K., 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33 (1), 3-56.

Falkenstein, E. G., 1996. Preferences for stock characteristics as revealed by mutual fund portfolio holdings. *Journal of Finance*, 51, 111-135

Gompers, P. A., Metrick, A., 2001. Institutional investors and equity prices. *Quarterly Journal of Economics*, 116, 229-259

Garcia, D., Mantilla-Garcia, D., Martellini, L., 2014. A model-free measure of aggregate idiosyncratic volatility and the prediction of market returns. *Journal of Financial and Quantitative Analysis*, 49, 1133-1165.

Gu, M., Kang, W., Xu, B., 2018. Limits of arbitrage and idiosyncratic volatility: Evidence from China stock market. *Journal of Banking & Finance*, 86, 240-258.

Gu, M., Jiang, G.J., Xu, B., 2019. The role of analysts: An examination of the idiosyncratic volatility anomaly in the Chinese stock market, *Journal of Empirical Finance*, 52, 237-254.

Kotkatvuori-Ornberg, J., Nikkinen, J., Ajio, J., 2013. Stock market correlations during the financial crisis of 2008–2009: evidence from 50 equity markets. *International Review of Financial Analysis*, 28, 70-78.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. *Journal of Financial Economics*, 32(1), 23-43.

Nartea, G. V., Wu, J., Liu, Z., 2013. Does idiosyncratic volatility matter in emerging markets? Evidence from China. *Journal of International Financial Markets, Institutions & Money*, 27, 137-160.

Shan, Y., Taylor, S., Walter, T., 2014. The role of "other information" in analysts' forecasts in understanding stock return volatility. *Review of Accounting Studies*, 19, 1346–1392.

Xie, F., Anderson, H.D., Chi, J., Liao, J., 2019. Does residual state ownership increase stock return volatility? Evidence from China's secondary privatization. *Journal of Banking & Finance*, 100, 234-251.

Rizvi, S.A., Arshad, S., Alam, N., 2018. A tripartite inquiry into volatility-efficiency-integration nexus - case of emerging markets. *Emerging Markets Review*. 34, 143-161.

Tian, S., Wu, E., Wu, Q., 2018. Who exacerbates the extreme swings in the Chinese stock market? *International Review of Financial Analysis*, 55, 50-59.

Vogelsang, T. 1998. Trend Function Hypothesis Testing in the Presence of Serial Correlation. *Econometrica*, 66, 123-48.

Wan, X., 2018. Is the idiosyncratic volatility anomaly driven by the MAX or MIN effect? Evidence from the Chinese stock market, *International Review of Economics & Finance*, 53, 1-15.

Wang, K., Chen, Y.H., Huang, S.W., 2011. The dynamic dependence between the Chinese market and other international stock markets: A time-varying copula approach. *International Review of Economics & Finance*, 20 (4), 654-664.

Xu, Y., Malkiel, B.G. 2003. Investigating the Behavior of Idiosyncratic Volatility. *Journal of Business*, 76, 613–44.

Appendix

Appendix A

Table A-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 construction industry tend 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 other 13 industry-specific volatility series.

Table A-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 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 A-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 A-3 Lags of dynamic FIRM 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 B

Table B-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 (26) or Fama-French three factors model in equation (27). 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 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					