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The economic sources of China's CSI 300 spot and futures volatilities before and after the 2015 stock market crisis

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ABSTRACT

The 2015 Chinese stock market crisis has increased focus on the factors that determine the volatility of stock spot and futures markets. In this paper, we investigate the economic sources of CSI 300 spot and futures volatilities before and after the stock market crash based on the generalized autoregressive conditional heteroskedasticity model with the mixed frequency data sampling scheme (GARCH-MIDAS). It shows that the risks of the CSI 300 Index tend to increase with higher inflation, lower economic growth, tighter credit conditions and more variant credit policies, while the risks of CSI 300 futures tend to increase with higher inflation, tighter credit conditions, more variant inflation rates and more variant credit policies. The effects of economic fundamentals are greater and more prolonged than the effects of economic uncertainty and speculative trading. Investors are advised to pay attention to the changes in price levels, economic development and credit policies when managing their portfolio risks. More importantly, as speculation has contributed little to the risks of CSI 300 futures in the post-crisis period, regulators are advised to ease trading restrictions and resume index futures trading gradually.

1. Introduction

Understanding the origins of stock market volatility has long been a topic of considerable interest. The Chinese stock market crash in summer 2015 has brought this issue back into the spotlight of both policymakers and market participants. The CSI 300 Index, which represents the broad A-share market, reached a high of 5353 at the beginning of June and subsequently collapsed to 3342 at the end of August, slumping 2000 points in 3 months. Under tremendous pressure from both regulators and the public, on August 26 and September 7, the China Financial Futures Exchange (CFFEX) adopted two rounds of harsh restrictions to curb speculative trading in stock spot and futures markets, such as identifying abnormal trades, increasing margins for non-hedging trading and raising the clearing fees for intraday trades.

Has speculative trading stopped as a result of these regulatory measures? In other words, do speculative factors continue to affect stock market volatility even after imposition of harsh regulations? These questions have motivated us to investigate the economic sources of CSI 300 spot and futures volatilities before and after the 2015 stock market crash. This topic is important for policymakers, as it evaluates the necessity of resuming index futures trading restrictions. For example, if economic fundamentals dominate speculation as the key factors causing stock volatility, regulators should consider relaxing trading restrictions on stock index futures. If speculation

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continues to play an important role in stock market fluctuations despite the regulations, regulators are advised to implement more restrictive measures. Moreover, this topic is interesting for investors, as understanding the economic sources of stock volatility helps them to forecast the market portfolio risks. Clearly, the great turmoil that ensued after the 2015 stock market crash brought about unexpected losses to most investors. The findings of this paper may provide them with new ideas to improve their forecast of stock spot and futures volatilities in risk management.

In prior studies, the economic sources of stock volatility are divided into three types: economic fundamentals, economic uncertainty and speculation (Asai, Caporin, & McAleer, 2015). Economic fundamentals are helpful in explaining why stock volatility changes over time, as stressed in Schwert (1989). Among them, price level (consumer price index or producer price index), real economy development (gross domestic production or industrial production growth) and monetary policy (interest rate or credit loan growth) are frequently used to explain stock market volatility. Examples can be found in Engle and Rangel (2008), Pierdzioch, Döpke, Hartmann. (2008), Asgharian, Hou, and Javed (2013), Corradi, Distaso, and Mele (2013), Girardin and Joyeux (2013), Asgharian, Christiansen, and Hou (2016), Conrad and Loch (2015) and Yang, Cai, and Hamori (2018) (Asgharian et al., 2016). Economic uncertainty, measured by the innovations from autoregressive models of economic data, is also closely linked with stock market volatility. The uncertainty in price level, real economy, monetary policy and exchange rate are considered in studies such as Morelli (2002), Beltratti and Morana (2006), Diebold and Yilmaz (2008), Paye (2012) and Engle, Ghysels, and Sohn (2013) (Asgharian et al., 2013). Speculation is another cause of stock market volatility, as mentioned in Mei, Scheinkman, and Xiong (2009), Yang, Yang, and Zhou (2012) and Bohl, Diesteldorf, and Siklos (2015). Speculative activity is often measured by trading volume or turnover, as is evident in Wen and Yang (2009), Girardin and Joyeux (2013), Floros and Salvador (2016), Caginalp and DeSantis (2017), Gao and Yang (2017).

Overall, most of these studies examine the stock spot market rather than the stock index futures market, and the possible changes in economic sources before and after the 2015 market crash are rarely evaluated. Few of the studies explore the three economic sources simultaneously, except for Girardin and Joyeux (2013). Therefore, this paper is designed to examine the economic sources of stock spot and futures volatilities in a unified framework, and then compare their differences before and after the 2015 stock market crisis. The CSI 300 spot and futures are examined, as the CSI 300 Index represents the broad A-share market and CSI 300 futures are China's most actively traded futures contracts. Furthermore, a generalized autoregressive conditional heteroskedasticity model with the mixed data sampling scheme (GARCH-MIDAS) is adopted, as the stock spot and futures volatilities are observed daily while the economic source factors are observed on a monthly basis.

The findings of this paper complement the literature on the economic sources of stock volatilities. We apply the GARCH-MIDAS model proposed by Engle et al. (2013) to analyzing the impact of economic sources on the volatilities of the CSI 300 Index and CSI 300 futures. Among the three types of economic sources, economic fundamentals have the most influential and persistent impact on CSI 300 spot and futures volatilities, which are followed by speculation and economic uncertainty. Furthermore, speculative factors contribute less to the risks of the futures market after the harsh restriction measures.

In addition, this paper provides additional Chinese empirical evidence on derivatives regulations during the market crisis. While researchers such as Kleidon and Whaley (1992) and Ghysels and Seon (2005) have analyzed futures trading regulations in the U.S. and East Asian countries, few have investigated the latest stock market plunge in China. An exception is Han and Liang (2017), who examine the effects of index futures trading restrictions from the perspective of stock market liquidity. They show that restrictions placed on CSI 300 and CSI 500 index futures trading during the 2015 market crisis cause a deterioration in spot market quality. However, in this paper, we evaluate the impact of index futures trading restrictions from the perspective of market fluctuations. It appears that the harsh restrictions on index futures trading during the stock market plunge have only ruled out speculative trading in CSI 300 futures but have failed to prevent speculative activity from the CSI 300 Index. The speculative component in stock spot market appears to be stronger after the restrictive measures, suggesting that the restrictive measures on futures trading no longer exclude speculative activity in stock markets, and that it is time for regulators to ease the index futures trading.

Girardin and Joyeux (2013) also use a GARCH-MIDAS model to study A-share stock volatility. This paper differs from theirs in the following three ways. First, while we use a GARCH-MIDAS model with explanatory variables, they use a GARCH-MIDAS model without exogenous variables. Second, we examine both stock spot and futures markets before and after the 2015 stock market crash, whereas they study the A- and B-share markets before 2010. Third, we compute the contributions of each type of economic source to the volatilities of CSI 300 Index and futures, but they do not.

This paper is organized as follows. Section 2 presents the GARCH-MIDAS model. Section 3 describes the data, including the daily returns and monthly economic factors. Section 4 investigates the economic source of the CSI 300 spot and futures volatilities. Section 5 provides the robustness analysis. Section 6 concludes the paper.

2. GARCH-MIDAS model with explanatory variables

The volatilities of the CSI 300 Index and CSI 300 futures are usually observed daily, while the economic source factors are observed on a monthly basis. The conventional approach is to transform daily volatility into monthly volatility and then to regress monthly volatility on the economic source factors, thus missing the intramonth information. To overcome this problem, Engle et al. (2013) propose a GARCH-MIDAS model with explanatory variables. The model enables us to investigate the impact of monthly economic factors on daily CSI 300 spot or futures volatilities without losing any intra-month information.

The GARCH-MIDAS model used in this paper differs from Girardin and Joyeux's (2013) model, as they use a "pure" GARCH-MIDAS model without any explanatory variables. The monthly long-run volatilities of Chinese A- and B-share markets are extracted based on the model and are regressed on monthly economic factors. The cointegration relationship between long-run volatility and economic factors are reparameterized as error correction models, and the lagged effects of economic variables are considered by including the second-order lags. The GARCH-MIDAS model in this paper, however, directly incorporates the economic variables into the evolution of volatility. It is not necessary to account for the cointegration relationship between long-run volatility and economic factors. Moreover, it allows us to examine the prolonged lagged effects of economic factors in a flexible but parsimonious manner (not limited to second-order lags).

Let $r_{i,t}$ be the daily return of the CSI 300 Index or CSI 300 futures on day i in month t. Each month has N_t days. $r_{i,t}$ is assumed to have a constant mean μ and time-varying conditional volatility:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \quad \forall i = 1, \cdots, N_t, \tag{1}$$

where $\varepsilon_{i,t}$ is identically and independently distributed as $N(0,1)$ with the information set up to day $(i-1)$ of month t. The conditional volatility of $r_{i,t}$ is decomposed into two components: $g_{i,t}$ is the short-run component accounting for daily fluctuations and τ_t is the long-run secular component assumed to be fixed for month t.

The short-run volatility $g_{i,t}$ is given in equation (Asgharian et al., 2016). Its dynamic mechanism is similar to the GARCH (Asai et al., 2015) process with parameters $0 < \alpha, \beta < 1$ and $\alpha + \beta < 1$:

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t}. \tag{2}$$

The long-run volatility τ_t is given in equation (Asgharian et al., 2013). It has a log version to ensure its positivity and is assumed to be affected by the K-month lags of monthly economic factors $X_{q,t}$ for $q = 1, \cdots, Q$. For either the CSI 300 Index or CSI 300 futures, we examine $Q = 7$ economic source factors, including economic fundamentals, economic uncertainty and speculation (discussed in Section 3). The intercept is c and the slope and weight coefficients are (θ_q, ω_q), for $q = 1, \cdots, Q$.

$$\begin{aligned} \log\tau_t &= c + \theta_1\sum_{k=1}^{K}\varphi_k(\omega_1)X_{1,t-k} + \cdots + \theta_Q\sum_{k=1}^{K}\varphi_k(\omega_Q)X_{Q,t-k}, \\ &= c + \sum_{q=1}^{Q}\left[\theta_q\sum_{k=1}^{K}\varphi_k(\omega_q)X_{q,t-k}\right]. \end{aligned} \tag{3}$$

$\varphi_k(\omega_q)$ is the beta function $\varphi_k(\omega; K) = (1-k/K)^{\omega-1}/\sum_{k=1}^{K}(1-k/K)^{\omega-1}$, which is a weight scheme giving higher (lower) weights to nearby (distant) $X_{q,t}$. The impact of $X_{q,t}$ on τ_t can be examined by plotting the weight function $\varphi_k(\omega_q)$ for $k = 1, \cdots, K$. For fixed K, the lower the ω_q value, the longer the influence of $X_{q,t}$ lasts.

The model is estimated using a maximization likelihood estimation. As the value of log-likelihood function depends on the MIDAS lag K, it is necessary to choose the optimal lag via profiling of the likelihood function. The approach is to select the smallest number of MIDAS lags after which the log-likelihood values seem to reach the plateau, which is also used in Engle et al. (2013) and Colacito, Engle, and Ghysels (2011).

3. Data

This paper investigates the daily volatilities of the CSI 300 Index (CSI) and CSI 300 futures (IF). The daily closing prices of the CSI 300 Index and CSI 300 futures are from April 16, 2010 to July 31, 2018. The sample from April 16, 2010 to September 30, 2016 is used for in-sample estimation and the observations from October 1, 2016 to July 31, 2018 are used for out-of-sample forecast. To construct the continuous nearby futures price series, we use the prices for the nearby futures contract until the contract reaches the first day of the delivery month. Prices for the next nearby contract are then used. The daily return is $r_{i,t} = 100 \times (\log P_{i,t} - \log P_{i-1,t})$, where $P_{i,t}$ is the price on day i of month t for CSI or IF.

This paper also evaluates whether monthly economic factors have any impact on the stock spot and futures volatilities. Monthly economic data are taken from April 2010 to July 2018. All of the data are sourced from CSMAR Solution provided by GTA Finance and Education Group and Wind Financial Terminal.

There are three monthly economic fundamental factors: inflation rate (*CPI*, growth rate of consumer price index), industrial production growth rate (*IP*) and credit growth rate (*CRD*). Both *CPI* and *IP* are seasonally adjusted. *CRD* is the log difference of monthly bank credit (multiplied by 100), as bank credit plays an important role in Chinese stock market comovement (Girardin & Liu, 2005).

There are three monthly economic uncertainty factors: uncertainty in price level (*CPIvol*), uncertainty in real economy (*IPvol*) and uncertainty in credit policy (*CRDvol*). Of these, *CPIvol* is the squared residual estimated by fitting an AR (12) model with 11 monthly dummy variables to *CPI*. The same approach also applies to *IPvol* and *CRDvol*, as in Schwert (1989), Girardin and Joyeux (2013) and Engle et al. (2013).

The monthly speculative factor is measured by the squared unexpected trading volume (*PFVM*), which is known as persistent free trading volume. Following Wen and Yang (2009), it can be calculated in three steps. First, take logarithm to an original monthly trading volume to obtain a processed sequence of trading volume VM_t. Second, regress VM_t on time trend t and t^2 to get the residual VM'_t. Third, model VM'_t by ARMA (1,1) and GARCH(1,1) models and obtain the squared standardized residual $PFVM_t$. As mentioned in Gallant, Rossi, and Tauchen (1992), Wen and Yang (2009), $PFVM_t$ is a trading volume which is filtered out time trend, autocorrelation and clustering of volatility. It measures the unexpected information shock to trading volume that is possible caused by speculative activities.

If there is excessive speculation among investors, the values of $PFVM_t$ will probably increase. In our empirical analysis, the persistent free trading volume of the CSI 300 Index ($PFVM^{CSI}$) is used in the analysis of the CSI 300 Index volatility, and the persistent free trading volume of the dominant CSI 300 futures contracts ($PFVM^{IF}$) is used in the analysis of the CSI 300 futures volatility.

4. Empirical results

4.1. Descriptive statistics

Fig. 1 plots the daily returns of the CSI 300 Index and CSI 300 futures from April 16, 2010 to July 31, 2018. Both returns series co-move throughout the sample period, and the futures returns fluctuate somewhat more than the spot returns. Furthermore, both returns became much more volatile during the 2015 stock market crash.

Table 1 reports the summary statistics of daily returns and monthly economic variables for the in-sample period. To facilitate the investigation of stock volatilities before and after the crash, the sample is divided into two periods: sample 1 from April 16, 2010 to June 14, 2015 and sample 2 from July 15, 2015 to September 30, 2016. The mid-June turning point is chosen because the stock market collapsed on June 15, 2015, lost over 34% in 20 days and slumped 1000 points. Subsequently, on July 15, the Chinese government adopted a series of supportive measures to restrict high frequency program trading in stock index futures market. Han and Liang (2017) also use June 15, 2015 as the starting date of the crash period.

First, from Table 1, the prices of CSI 300 spot and futures decrease dramatically and become much riskier after the stock market plunge. Either CSI 300 spot or futures exhibits lower average returns but higher standard deviations on switching from sample 1 to sample 2. For example, the CSI 300 Index return decreases from 0.0361 to −0.1546 on average, but its standard deviation rises from 1.4247 to 2.2250, implying higher risks after the market crash. The results coincide with Wang, Jiang, Lin, Xie, and Stanley (2018), who show that the systematic risks of financial markets reach a peak during the 2015–2016 stock market turbulence. For the whole in-sample period, the CSI 300 Index generally yields higher returns but lower risks than CSI 300 futures. Both returns are non-normally distributed with negative skewness and excess kurtosis, indicating a higher probability of a market crash than a market boom. Similar features of CSI 300 spot and futures can be found in Wang and Xie (2013), who analyze the high-frequency cross-correlations between the spot and futures markets from 2010 to 2012.

Second, most of the economic fundamental and uncertainty variables drop after the stock market plunge, except for the credit policy uncertainty. The growth rate of price level is slower (*CPI* from 3.0654 to 1.8147) and less variant (*CPIvol* from 8.4848 to 7.8223). The development of a real economy also slows down (*IP* from 10.8611 to 6.1067) and its unexpected uncertainty is reduced (*IPvol* from

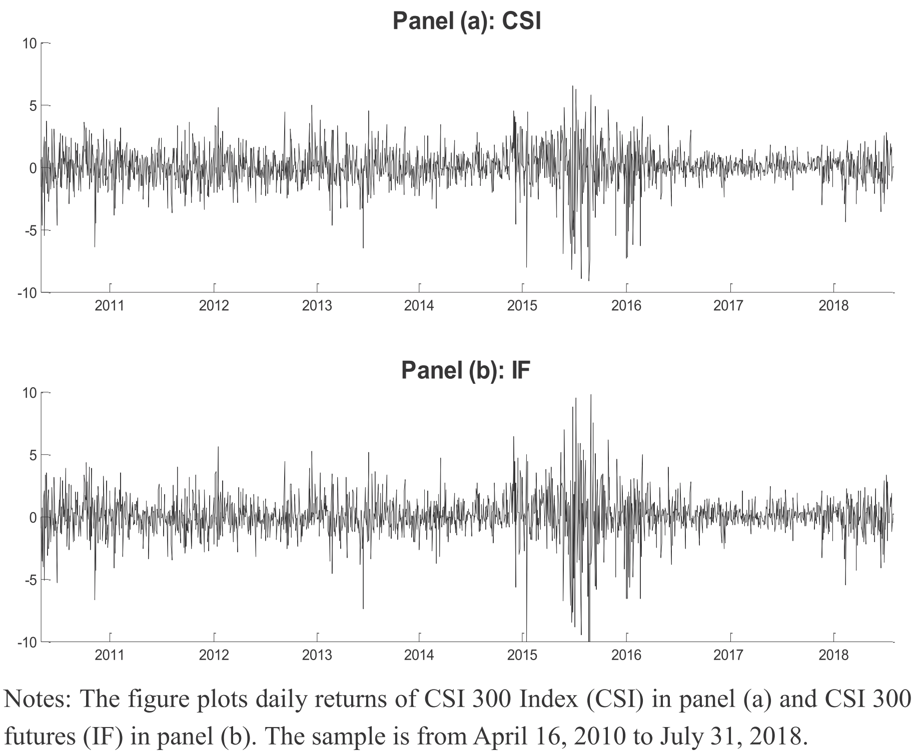


Fig. 1. Daily CSI 300 Index and CSI 300 futures returns.
Notes: The figure plots daily returns of CSI 300 Index (CSI) in panel (a) and CSI 300 futures (IF) in panel (b). The sample is from April 16, 2010 to July 31, 2018.

Table 1
Summary statistics of daily returns and monthly economic variables.

		Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16 –2016/9/30	2010/4/16 –2015/6/14	2015/6/15 –2016/9/30	2010/4/16 –2016/9/30	2010/4/16 –2015/6/14	2015/6/15 –2016/9/30
				$r_{i,t}^{IF}$		
Mean	−0.0027	0.0361	−0.1546	−0.0039	0.0352	−0.1568
Std.	1.6209	1.4247	2.2250	1.8276	1.5112	2.7318
Skew.	−0.7098	−0.2825	−0.9409	−0.3506	−0.1166	−0.3233
Kurt	4.2782	2.5926	3.1580	6.0209	4.0995	3.2187
Nobs	1572	1252	320	1572	1252	320
				IP		
Mean	2.8249	3.0654	1.8147	9.9468	10.8611	6.1067
Std.	1.4043	1.4556	0.3319	3.4291	3.1886	0.2884
Skew	1.0570	0.7823	0.0912	0.7842	0.7545	0.4931
Kurt	0.1460	−0.3848	−0.9202	0.2319	0.4714	0.7093
Nobs	78	63	15	78	63	15
				CPIvol		
Mean	1.1295	1.1635	0.9865	8.3681	8.4848	7.8223
Std.	0.4154	0.3710	0.5589	14.6296	16.1839	3.9777
Skew	1.3332	1.6651	1.3238	3.9748	3.6291	0.7433
Kurt	3.6415	5.4107	1.5347	17.2276	13.7184	−0.2269
Nobs	78	63	15	78	63	15
				CRDvol		
Mean	9.9468	2.7622	0.9177	0.1560	0.1441	0.2015
Std.	3.4291	4.7077	0.5497	0.3190	0.3398	0.2054
Skew	0.7842	2.1154	0.1304	4.8426	5.0075	0.8330
Kurt	0.2319	3.5712	−1.3266	27.5151	27.1086	−0.8118
Nobs	78	63	15	78	63	15
				$PFVM^{IF}$		
Mean	1.0685	1.1193	0.8548	1.3186	1.3311	1.2657
Std.	2.5408	2.7976	0.8865	2.9419	2.6464	4.0720
Skew	4.8051	4.4207	1.0430	4.0537	4.1668	3.4675
Kurt	23.9058	19.4752	−0.1729	17.2514	20.0138	10.0420
Nobs	78	63	15	78	63	15

Notes: $r_{i,t}^{CSI}$ and $r_{i,t}^{IF}$ are the daily returns of CSI 300 Index and CSI 300 futures. The rest are monthly economic variables: *CPI* is inflation rate, *IP* is industrial production growth rate, *CRD* is credit growth rate, *CPIvol* is uncertainty in inflation, *IPvol* is uncertainty in industrial production growth, *CRDvol* is uncertainty in credit growth, $PFVM^{CSI}$ is persistent free trading volume of CSI 300 Index, and $PFVM^{IF}$ is persistent free trading volume of CSI 300 futures. Std is standard deviation, Skew is skewness, Kurt is excess kurtosis and Nobs is number of observations.

2.7622 to 0.9177). It is inferred that a recession in a real economy is closely linked with a recession in financial markets. The central bank tightens its credit policy with *CRD* from 1.1635 to 0.9865 to restrict any arbitrage activities in stock markets. However, the unexpected shock to the credit policy is driven up (*CRDvol* from 0.1441 to 0.2015), possibly because investors never expect the government to impose harsh credit restrictions after the market crash.

Lastly, speculative trading volumes in both spot and futures markets decrease after the regulatory measures of curbing index futures trading are adopted. The persistent free trading volume, as in Wen and Yang (2009), is regarded as a proxy for information flow, which causes price changes. $PFVM^{CSI}$ decreases from 1.1193 to 0.8548 and $PFVM^{IF}$ decreases from 1.3311 to 1.2657, implying that speculative trading has been well regulated after the stock market plunge.

4.2. Volatility decomposition of CSI 300 spot and futures

Table 2 shows the in-sample estimates of the GARCH-MIDAS models for the CSI 300 Index and CSI 300 futures from April 16, 2010 to September 30, 2016. Fig. 2 plots the estimated volatility of the CSI 300 Index in Panel (a) and the estimated volatility of CSI 300 futures in Panel (b). The black solid line is the conditional volatility $\tau_t g_{i,t}$ in equation (Asai et al., 2015), which is the product of long-run component τ_t and short-run component $g_{i,t}$, and the red dotted line is the long-run volatility τ_t.

In Table 2, for either the CSI 300 Index or CSI 300 futures, the long-run volatility intercept *c* becomes much higher in sample 2 than in sample 1, which is consistent with the findings of higher standard deviations after the market crash in Table 1. Moreover, in Fig. 2, the volatilities of the CSI 300 Index and CSI 300 futures rise dramatically in the middle of 2015. Only part of the increased volatility is explained by the long-run component, as the long-run volatility does not fluctuate as much as the overall volatility during the stock crisis.

Also, Table 2 reveals that the volatilities of CSI 300 spot and futures become less persistent after the market crash, implying more information is integrated into the spot and futures prices. The sums of ARCH coefficients (α and β) decrease from 0.9276 to 0.8387 for the CSI 300 Index and from 0.9286 to 0.7777 for CSI 300 futures. In Lamoureux and Lastrapes (1990), $\alpha+\beta$ measures the contribution

Table 2
In-sample estimates of GARCH-MIDAS models.

	Panel (a) CSI			Panel (b) IF		
		Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30
	0.0284	0.0292	0.0335	0.0154	0.0102	0.0511
	(0.0515)	(0.0364)	(0.0663)	(0.0246)	(0.0149)	(0.0816)
	0.0217	0.0238*	0.0152	0.0474***	0.0520***	0.0386
	(0.0132)	(0.0123)	(0.0193)	(0.0151)	(0.0170)	(0.0398)
	0.9031***	0.9038***	0.8235***	0.8757***	0.8766***	0.7391***
	(0.0345)	(0.0352)	(0.0245)	(0.0357)	(0.0372)	(0.0281)
	1.8506***	1.4940***	2.9746***	2.2875***	2.2008***	3.3369***
	(0.3948)	(0.3477)	(0.2219)	(0.5280)	(0.5166)	(0.1779)
	1.3904*	1.7908**	0.9675*	1.4606**	1.8905***	1.3393**
	(0.7202)	(0.8162)	(0.5465)	(0.6197)	(0.5383)	(0.6531)
	−1.0709**	−0.2360	−5.8609***	−1.2895	−0.1571	−0.0183
	(0.4929)	(0.4916)	(1.9331)	(1.2365)	(0.1010)	(0.0312)
	−3.0152***	−1.5744***	−3.5301***	−4.5045***	−2.8144***	−7.5785**
	(1.0228)	(0.3822)	(1.1003)	(1.3384)	(1.0676)	(3.6875)
	0.0337**	0.0476*	−0.1196	0.0372*	0.0327*	0.0405**
	(0.0148)	(0.0254)	(0.1252)	(0.0202)	(0.0167)	(0.0203)
	1.6969	1.0709	2.3601	0.0929**	0.1410*	0.0790
	(1.8795)	(0.9857)	(4.9162)	(0.0447)	(0.0804)	(0.1114)
	1.8180**	2.0579**	1.7522*	1.3325**	0.9182*	1.4529**
	(0.8021)	(0.8165)	(0.9260)	(0.5779)	(0.5215)	(0.6066)
	6.2876***	5.4473***	6.3506***	7.0145***	6.9593***	10.1139
	(1.7737)	(0.7141)	(2.0610)	(1.8403)	(2.0735)	(9.1867)
	7.6298**	6.3296**	8.6425**	7.5412**	7.7988*	5.3428**
	(3.2306)	(2.7874)	(3.8225)	(3.7762)	(4.0716)	(2.1342)
	9.2675*	1.5350	10.5914**	6.7028	6.0200	8.1494
	(5.3801)	(1.2638)	(5.0552)	(5.2266)	(5.5014)	(5.7984)
	7.2284**	7.7375***	6.6461***	7.806***	6.6689***	8.6151**
	(2.8601)	(2.9646)	(2.1796)	(2.5740)	(1.5339)	(3.3719)
	12.8555**	13.4163**	1.8788	15.4082**	16.3348***	11.9152**
	(6.3005)	(6.2794)	(1.6619)	(6.5443)	(6.1640)	(5.6080)
	9.3449	9.9934	7.0373	16.9050**	18.6264**	11.6415
	(8.9896)	(10.1572)	(4.4788)	(8.0372)	(7.5204)	(7.9086)
	12.6014**	9.5296**	13.4189**	15.2405***	17.6911***	10.7782*
	(5.5782)	(4.7700)	(6.3168)	(4.8297)	(3.8680)	(6.2324)
	14.0154***	12.3113***	20.1389**	24.3739***	27.3643***	10.1139
	(5.1044)	(4.0401)	(8.7979)	(9.2459)	(9.7725)	(9.7725)
	48	48	12	48	48	12
logL($\times 10^3$)	−2.7880	−2.1539	−0.6159	−2.8937	−2.1998	−0.6642
AIC($\times 10^3$)	5.6081	4.3358	1.2598	5.8195	4.4316	1.3525
BIC($\times 10^3$)	5.6938	4.4076	1.3125	5.9053	4.5137	1.3977
MAE	0.9553	0.7377	1.2850	1.2353	0.8810	1.5564
MSE	1.1294	0.5369	1.9748	2.1584	0.8973	2.1381

Notes: The table reports the in-sample estimates of GARCH-MIDAS models from April 16, 2010 to September 30, 2016, with CSI 300 Index (CSI) in panel (a) and with CSI 300 futures (IF) in panel (b). Brackets below are standard errors. ***, **, * denote significance at the 1%, 5% and 10% levels. The values of log likelihood (logL) and the information criteria (AIC, BIC) are given. The last two rows are the goodness-of-fit measures, where MAE is the mean absolute error of estimated conditional volatility and the true volatility with squared return as a proxy, and MSE is the mean squared error of the two volatilities.

of lagged squared residuals and reduced $\alpha+\beta$ implies that additional information about return variance is accounted for. Therefore, the reduced $\alpha+\beta$ suggests that more information is integrated into the volatilities of CSI 300 spot and futures after the market crash. Similar findings can be observed in the study of gold markets during the global financial crisis in Wang, Xie, Jiang, and Stanley (2016).

Last, the GARCH-MIDAS models perform better in stock index than in stock index futures, and they perform better in the pre-crisis period than in the post-crisis period. Following Hou and Suardi (2012), Hou (2013), we calculate the goodness-of-fit measures at the bottom of Table 2, where MAE is the mean absolute error of the estimated conditional volatility and the true volatility with squared return as a proxy, and MSE is the mean squared error of the estimated conditional volatility and the true volatility. It is shown that MAE

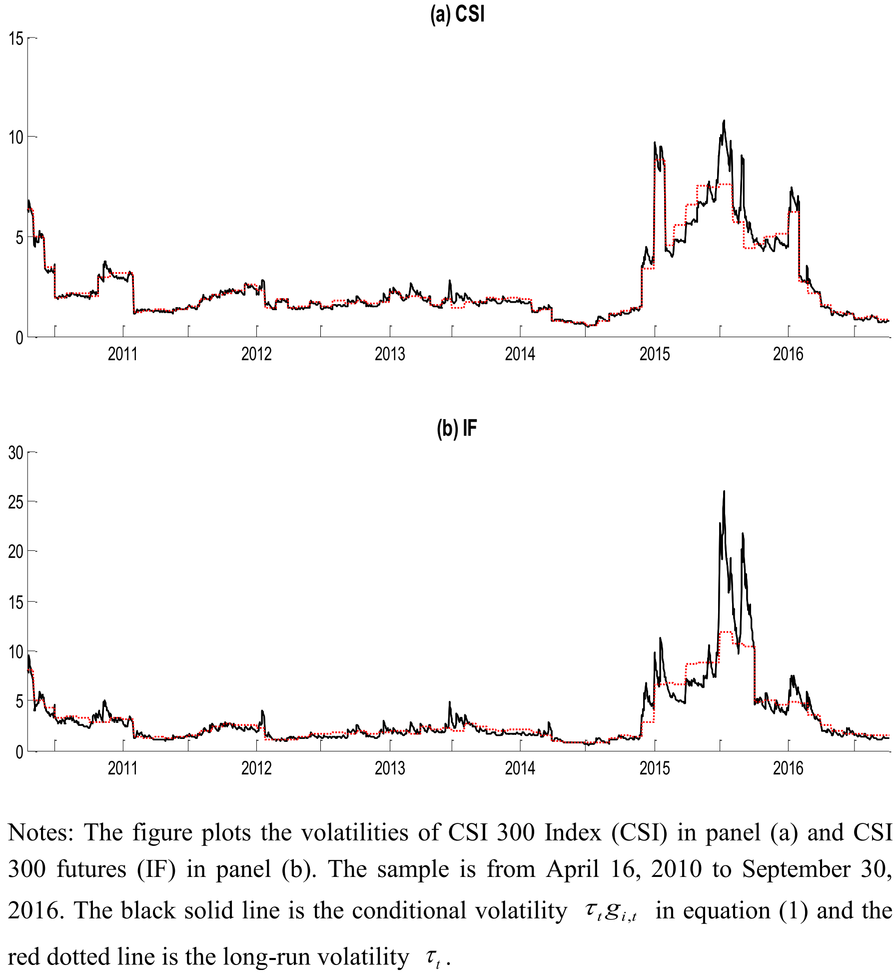


Fig. 2. Volatility decomposition of CSI 300 Index and CSI 300 futures

Notes: The figure plots the volatilities of CSI 300 Index (CSI) in panel (a) and CSI 300 futures (IF) in panel (b). The sample is from April 16, 2010 to September 30, 2016. The black solid line is the conditional volatility $\tau_t g_{i,t}$ in equation (Asai et al., 2015) and the red dotted line is the long-run volatility τ_t. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

and MSE in CSI 300 futures are higher than in the CSI 300 Index, which indicates that the volatilities of stock index futures are more difficult to describe than the volatilities of stock index. It also shows that both MAE and MSE are higher in sample 2 than in sample 1, which tells us that the volatilities are more difficult to measure in times of crisis with fewer observations.

4.3. Economic sources of CSI 300 spot and futures volatilities

Table 2 also reports the individual impact of each economic factor on stock index and futures volatilities from April 16, 2010 to September 30, 2016. As in equation (Asgharian et al., 2013), θ_q measures how much impact the economic variable has on volatility, and ω_q measures how long the impact lasts, for $q = CPI, IP, CRD, CPIvol, IPvol, CRDvol, PFVM$. Fig. 3 plots the values of log-likelihood function using different lags K in equation (Asgharian et al., 2013). From Panels (a) and (d), for the whole in-sample period, the value of likelihood function of either the CSI 300 Index or CSI 300 futures increases with K, and it converges to the highest level at around 48 lags. We therefore limit K to be 48, which results in 4 MIDAS years. For the same reason, the optimal lag is chosen to be 48 for sample 1 and to be 12 for sample 2 from Panels (b), (c), (e) and (f). Fig. 4 plots the impacts of monthly economic factors on the long-run volatilities based on the values of ω_q.

First, higher inflation and lower credit growth drive up the volatilities of the CSI 300 Index and CSI 300 futures, while lower industry production growth only leads to higher CSI 300 Index volatility (Asai et al., 2015). Both the spot and futures markets have positive θ_{CPI} for the whole in-sample period. A percentage point increase in inflation raises the CSI 300 Index volatility by 1.3904% and CSI 300 futures volatility by 1.4606%. The estimates of θ_{CPI} decrease after the market crash, implying the effect of inflation on both volatilities gets increasingly weaker (Asgharian et al., 2016). While the CSI 300 Index volatility increases with a slow industrial growth rate, this is not so for CSI 300 futures. The negative θ_{IP} in CSI 300 Index suggests that the spot market reveal a countercyclical pattern between the

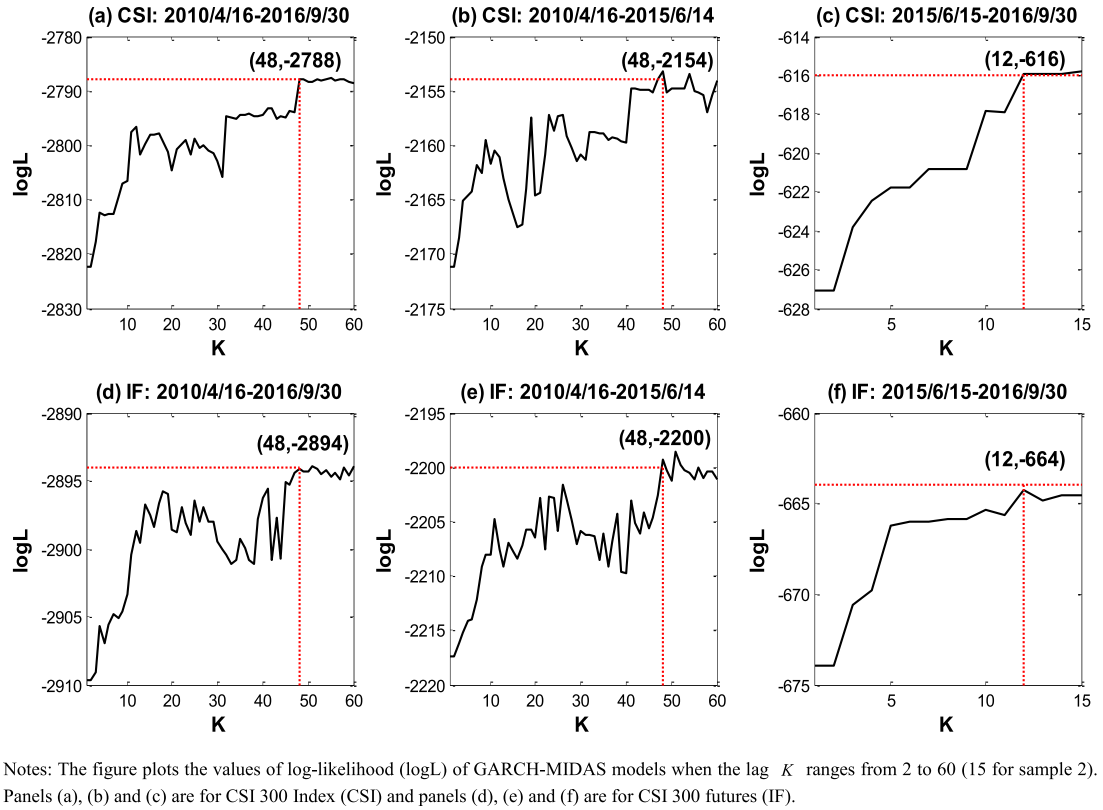


Fig. 3. Log-likelihood values of GARCH-MIDAS models

Notes: The figure plots the values of log-likelihood (logL) of GARCH-MIDAS models when the lag K ranges from 2 to 60 (15 for sample 2). Panels (a), (b) and (c) are for CSI 300 Index (CSI) and panels (d), (e) and (f) are for CSI 300 futures (IF).

real economy and financial markets, as mentioned in Engle et al. (2013) and Schwert (1989). Moreover, the negative impact of industrial production is much stronger in the post-crisis period. On the contrary, the futures market, with insignificant θ_{IP}, is disconnected from the real economy (Asgharian et al., 2013). A tightened credit policy raises the volatilities of the CSI 300 Index and CSI 300 futures with negative θ_{CRD}. A percentage point decrease in credit growth raises the CSI 300 Index volatility by 3.0152% and the CSI 300 futures volatility by 4.5045%. This is consistent with Paye (2012), wherein a commercial paper-to-treasury spread is used to proxy for credit condition. In both markets, the effect of credit contraction is amplified after the market plunge (Auerbach, 1982). The impacts of inflation, industrial production and credit policy last for 2 years. Fig. 4 (a), (b) and (c) plot the Beta weight function $\varphi_k(\omega_q)$ for $q = CPI$, IP, CRD, and their weights decay to zero at around 24-month lags. The long-lasting effects of bank credit on stock volatility coincide with Girardin and Liu (2005), who explore the effects of bank credit on the Shanghai and Shenzhen stock markets.

Second, higher inflation uncertainty and credit uncertainty drive up the spot and futures volatilities, while industrial growth uncertainty only affects the CSI 300 futures volatility (Asai et al., 2015). The estimates of θ_{CPIvol} are significantly positive but of limited magnitude for both markets. An increase of 1% in inflation uncertainty increases the spot volatility by 0.0337% and the futures volatility by 0.0372% (Asgharian et al., 2016). The estimates of θ_{IPvol} are only significantly positive for CSI 300 futures before the 2015 market crash, suggesting that the futures market is more likely to be linked with business cycle uncertainty, and that the linkage is stronger in market booms than in recessions. Similar results have been reported by Darrat and Rahman (1995) for the S&P 500 market and by Diebold and Yilmaz (2008) for over 40 international stock markets (Asgharian et al., 2013). Credit uncertainty (θ_{CRDvol}), unlike inflation uncertainty and industrial growth uncertainty, exerts a much larger impact on spot and futures volatilities. An increase of 1% in unexpected credit uncertainty increases the CSI 300 Index volatility by 1.8180% and the CSI 300 futures volatility by 1.3325%. Furthermore, after the stock market crash, credit uncertainty is less important to the spot market, but is more important to the futures market. The positive link between stock volatility and credit uncertainty is also reported in Beltratti and Morana (2006), who point out that high stock market volatility can be associated with an increase in money growth volatility (Auerbach, 1982). In Fig. 4 (d), (e) and (f), the uncertainty in inflation, industrial growth and credit policy influences the spot and futures volatilities for about 1 year (12 months), which is less persistent than the impact of economic fundamentals.

Third, speculative trading increases spot and futures volatilities, and when futures trading restrictions are imposed, the CSI 300 Index volatility becomes more sensitive to speculation, while the CSI 300 futures volatility becomes less sensitive to speculation (Asai et al., 2015). Positive estimates of θ^{CSI}_{PFVM} and θ^{IF}_{PFVM} indicate that speculation is one of the economic sources of spot and futures volatilities. A 1% increase in the CSI 300 Index speculative trading volume causes the spot volatility to increase by 6.2876%, and a 1%

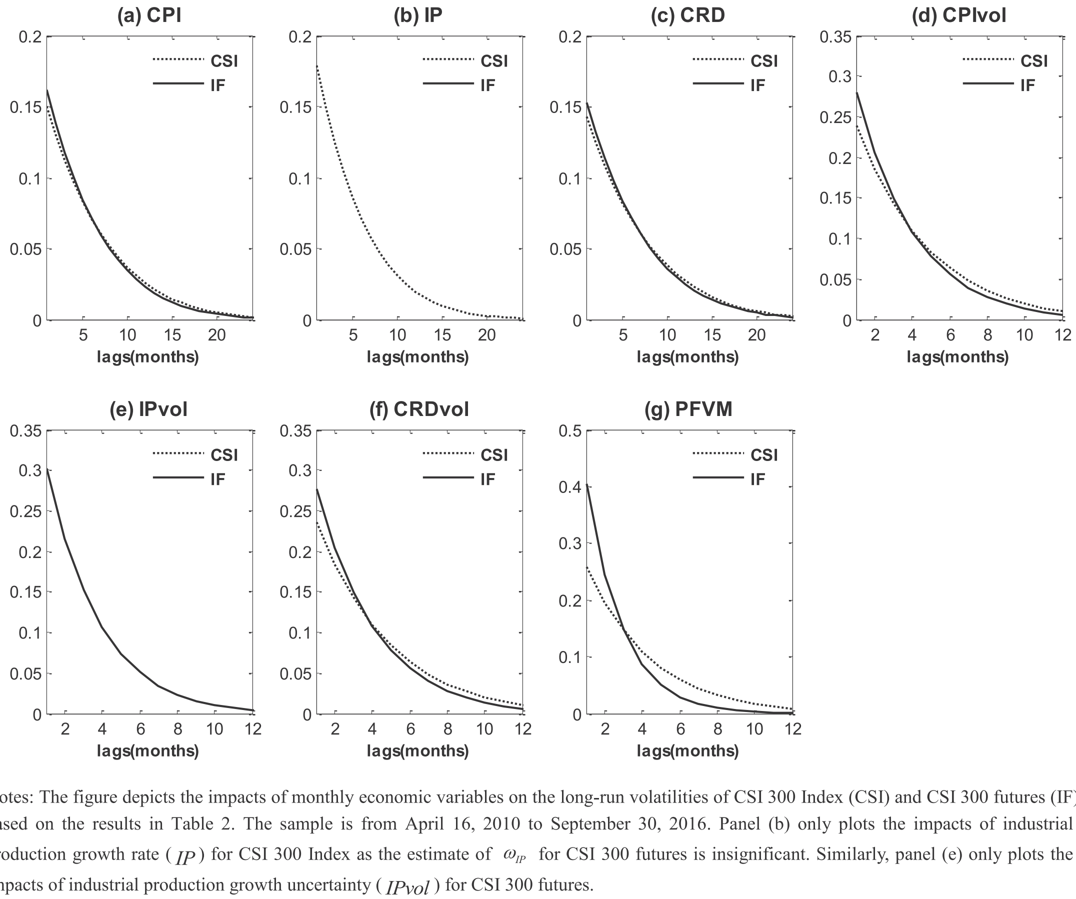


Fig. 4. Impacts of monthly economic variables on the volatilities of CSI 300 Index and CSI 300 futures
Notes: The figure depicts the impacts of monthly economic variables on the long-run volatilities of CSI 300 Index (CSI) and CSI 300 futures (IF) based on the results in Table 2. The sample is from April 16, 2010 to September 30, 2016. Panel (b) only plots the impacts of industrial production growth rate (*IP*) for CSI 300 Index as the estimate of ω_{IP} for CSI 300 futures is insignificant. Similarly, panel (e) only plots the impacts of industrial production growth uncertainty (*IPvol*) for CSI 300 futures.

increase in the CSI 300 futures speculative trading volume causes the futures volatility to increase by 7.0145%. The positive relation between stock volatility and lagged trading volume is also discussed in Gwilym, McMillan, and Speight (1999) and Chen, Firth, and Rui (2001). θ_{PFVM}^{IF} is higher than θ_{PFVM}^{CSI}, implying that the newly established futures market is more sensitive to overspeculation and market rigging (Asgharian et al., 2016). More importantly, the effect of speculative trading in the spot market always exists and becomes even stronger after the market plunge, while the impact of speculative trading in the futures market is only limited to the ex-crisis period. In other words, after the market crash and adoption of harsh restrictions on index futures trading, the futures market is no long sensitive to speculative trading. However, this is not the case for the spot market. The CSI 300 Index volatility are always responsive to speculative trading, even after the restrictive measures are implemented (Asgharian et al., 2013). From Fig. 4 (g), speculative trading is expected to influence the volatilities in the following 9–10 months, and its effects are much more short-lived than economic fundamentals and economic uncertainty.

Our results differ from the results in Girardin and Joyeux (2013). They point out that inflation, inflation uncertainty and credit uncertainty are the only three factors that are related with the A-share market volatility from 1996 to 2010. The duration of the impact does not exceed two months based on an error correction model. Unlike them, we employ the GARCH-MIDAS model by Engle et al. (2013) and incorporate all the economic factors into the evolution of volatility. It is found that after 2010 the economic sources of the stock spot and futures volatilities also come from other economic factors like industrial growth, credit policy uncertainty, and speculation, and their impact can last much longer.

4.4. Measuring the contributions of economic sources

How much of the stock index and futures volatilities can be explained by the three types of economic sources, namely, economic fundamentals, economic uncertainty and speculation? To answer this question, we follow Engle et al. (2013) and compute the ratio: $Var(\log \tau_t^{[m]}) / Var(\log(\tau_t g_{i,t}))$, where $\tau_t g_{i,t}$ is the GARCH-MIDAS volatility with all the 7 economic factors, and $\tau_t^{[m]}$ is the long-run volatility of a specific GARCH-MIDAS model m with only a subset of explanatory variables $X_{q,t}$, $q = CPI, IP, CRD, CPIvol, IPvol, CRDvol, PFVM$. The ratios reveal the contributions of each economic factor to the stock spot and futures volatilities.

Table 3 shows the variance ratios for the in-sample period and the two subsamples before and after the 2015 market crash. Overall, the in-sample results show that economic fundamentals have the most important contributions, which are followed by speculative factors and economic uncertainty. The comparison between the two subsamples reveals that the long-run economic factors contribute less to the stock spot and futures volatilities in sample 2 than in sample 1. For example, economic fundamentals explain 36.8284% of the CSI 300 Index volatility in sample 1 but only 30.7079% in sample 2. Similar patterns are found in economic uncertainty and speculation (except for speculation for the CSI 300 Index), implying that the risks of these two markets are driven up by more short-run fluctuations or information shocks after the market crash.

Economic fundamentals contribute 31.4098% of the CSI 300 Index volatility and 24.0845% of the CSI 300 futures volatility. Among the three economic fundamentals (CPI,IP,CRD), credit policy has the highest explanatory power. However, after the market crash, while the contributions of credit policy and price level decrease, the contributions of industrial growth increase. This pattern is more obvious in the spot market than in the futures market, suggesting that the recession in real economy drives up the risks of the stock spot market.

Economic uncertainty contributes only 5.8221% of the CSI 300 Index volatility and 10.1782% of the CSI 300 futures volatility. Uncertainty factors tend to explain more variations in futures markets than in spot markets, as futures prices contain information about investors' expectation of uncertainty in the future. Of the three economic uncertainty variables ($CPIvol$,$IPvol$,$CRDvol$,), the uncertainty in credit policy has the highest explanatory power. Since the market crash, its explanatory power has decreased for the CSI 300 Index but increased for CSI 300 futures, perhaps because the futures market with leverage is more likely to be affected by the unexpected tightened credit policy than the spot market.

Speculation contributes 18.3463% of the CSI 300 Index volatility and 20.6878% of the CSI 300 futures volatility. Furthermore, since the stock crisis, a greater proportion of the CSI 300 Index volatility has been explained by speculation (from 14.4052% to 20.5815%) while a much lower proportion of the CSI 300 futures volatility has been explained by speculation (from 31.8262% to 4.1324%), suggesting that the restrictive measures on futures trading have indeed had an effect on the futures market but not on the spot market. Speculation no longer causes risks in CSI 300 futures in the post-crisis period, but it is still responsible for the risks in spot markets.

4.5. Further implications to regulatory sectors and investors

As mentioned in the previous sections, speculative trading exerts lesser influence on the futures market but greater influence on the spot market after the adoption of trading restriction measures. Why does speculative trading behave so differently in spot and futures markets? This can be interpreted from the perspective of investors' trading incentives. In the first half of 2015, with a positive futures basis, investors such as hedgers or index arbitragers usually longed stock portfolios and shorted index futures. However, in the latter half of 2015, the CFFEX announced harsh trade restrictions on stock index futures and the futures basis became negative. As shorting futures became much more difficult, investors were suddenly exposed to huge systematic risks, and their only choice was to sell their stock shares as soon as possible after the CFFEX trading regulations were imposed. In this case, the CSI 300 futures volatility is unaffected by speculative trading, as futures trading is very thin. On the contrary, the CSI 300 Index volatility is more closely related to speculative trading, as most investors try to sell their stock shares to avoid underlying systematic risks.

Our findings on the impact of speculative trading provide the regulatory sectors with some policy suggestions, such as relaxing restrictions on index futures trading in a step-by-step manner. As shown in Fig. 2, the volatilities of the CSI 300 Index and CSI 300 futures have decreased since the second quarter of 2016, suggesting that the restrictive measures adopted by the CFFEX are effective in stabilizing the stock market. Moreover, as shown in Table 2, speculative trading contributes less to the risks of futures market after the

Table 3
In-sample evaluation of the economic sources contributions.

	Panel (a) CSI			Panel (b) IF		
		Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16 –2016/9/30	2010/4/16 –2015/6/14	2015/6/15 –2016/9/30	2010/4/16 –2016/9/30	2010/4/16 –2015/6/14	2015/6/15 –2016/9/30
Economic fundamentals						
	9.6584	12.8278	8.1558	6.8559	7.8719	3.9768
	7.8495	5.1144	9.3753	2.0805	0.0626	4.1324
	14.0128	17.7325	13.3194	14.6212	18.4129	12.8750
	31.4098	36.8284	30.7079	24.0845	26.4632	20.4154
Economic uncertainty						
	0.4991	0.5853	0.1451	2.2251	1.5422	2.8867
	0.0566	0.2557	0.0189	3.3473	4.2558	0.0826
	5.1041	6.3522	2.9160	4.8809	3.3708	5.9906
	5.8221	7.5012	3.1392	10.1782	10.4002	8.0048
Speculation: *PFVM*	18.3463	14.4052	20.5815	20.6878	31.8262	4.1324

Notes: The table reports the variance ratio $Var(\log \tau_t^{[m]})/Var(\log(\tau_t g_{i,t}))$ in percentage for CSI 300 Index (CSI) in panel (a) and for CSI 300 futures (IF) in panel (b), where m refers to a specific GARCH -MIDAS model with a subset of explanatory variables $X_{q,t}$, $q = CPI, IP, CRD, CPIvol, IPvol, CRDvol, PFVM^{CSI}, PFVM^{IF}$. The sample is from April 16, 2010 to September 30, 2016.

crisis, but it contributes more to the risks of spot market. Since stock market has always played a key role in Chinese financial markets, regulating speculations in stock market is also very important. To this end, it is time to ease trading restrictions and resume index futures trading. So far, the CFFEX has started to cut transaction fees, lower margin requirements for non-hedging accounts and increase the maximum limit on daily stock index futures trading. This is regarded as a preliminary sign of resuming index futures trading, but there is much room for further relaxation. Last but not least, as shown in Table 2, speculation remains a key component of the CSI 300 Index volatility. Hence, regulators are advised to implement the restrictions on index futures trading gradually to prevent the sudden increase in the risks of the spot and futures markets.

In addition, our findings provide some implications for investors in portfolio risk management. We conclude that the volatilities of the CSI 300 spot and futures are affected by economic fundamentals and economic uncertainty, and that the impact of economic fundamentals lasts longer than that of economic uncertainty. Investors should pay more attention to changes in the macroeconomic environment when evaluating their portfolio risks. Specifically, the risks of the CSI 300 Index, measured by volatility, are likely to rise with higher price levels, lower industrial production, tighter credit conditions and more variant credit policies, while the risks of CSI 300 futures are likely to rise with higher price levels, tighter credit conditions, more variant inflation rates and more variant credit policies. Furthermore, the effects of economic fundamentals on volatility can last for two years and are more prolonged than the effects of economic uncertainty and speculation.

4.6. *Out-of-sample performance*

We investigate the out-of-sample performance of the GARCH-MIDAS model in this sub-section. We assess the performance of volatility forecast in Section 4.6.1 and evaluate the performance of stock index and futures portfolios in Section 4.6.2. The out-of-sample forecast is constructed by a rolling window approach. The 2006 observations from April 16, 2010 to September 30, 2016 are used for the in-sample estimation, and the 445 observations from October 1, 2016 to July 31, 2018 are left for the out-of-sample forecast. On each day, we re-estimate the model using the past 2006 observations and do the one-day-ahead forecast. The procedure is repeated 445 times to produce 445 forecasts.

Besides the GARCH-MIDAS model in this paper, we consider another two models: GARCH in equation (Auerbach, 1982) and GARCH-MIDAS with realized volatility as explanatory variables (GARCH-MIDAS-RV) in equation (Baker, Bloom, & Davis, 2016). The latter also appears in Engle et al. (2013). Remember that $r_{i,t}$ is the daily return of the CSI 300 Index or CSI 300 futures on day i in month t.

GARCH:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \quad \forall i = 1, \cdots, N_t,$$

$$g_{i,t} = c + \alpha(r_{i-1,t} - \mu)^2 + \beta g_{i-1,t}. \tag{4}$$

GARCH-MIDAS-RV:

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}}\varepsilon_{i,t}, \quad \forall i = 1, \cdots, N_t,$$

$$g_{i,t} = (1 - \alpha - \beta) + \alpha\frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t}.$$

$$\tau_t = c + \theta\sum_{k=1}^{K}\varphi_k(\omega)RV_{t-k}, \quad RV_t = \sum_{i=1}^{N_t} r_{i,t}^2. \tag{5}$$

4.6.1. *Out-of-sample volatility forecast*

Table 4 reports the out-of-sample goodness-of-fit performance of volatility forecast. MAE is the mean absolute error of one-day-ahead

Table 4
Out-of-sample goodness-of-fit performance.

	Panel (a) CSI			Panel (b) IF		
	GARCH	GARCH -MIDAS-RV	GARCH -MIDAS	GARCH	GARCH -MIDAS-RV	GARCH -MIDAS
MAE	0.8265	0.9316	0.7003	1.2118	1.3557	1.1227
MSE	2.5525	2.6436	2.5448	5.7957	5.9584	5.6838
SPA p-value (MAE)	0.4905			0.5055		
SPA p-value (MSE)	0.1450			0.4980		

Notes: The table reports the out-of-sample goodness-of-fit performance from October 1, 2016 to July 31, 2018, with CSI 300 Index (CSI) in panel (a) and with CSI 300 futures (IF) in panel (b). MAE is the mean absolute error of one-day-ahead predicted conditional volatility and the true volatility with squared return as a proxy, and MSE is the mean squared error of the two volatilities. The last two rows are the p values of Hansen (2005)'s superior predictive ability (SPA) test statistics with MAE and MSE as loss functions. The null hypothesis is that the benchmark model (GARCH-MIDAS) is not outperformed by any of the other two competing models (GARCH, GARCH-MIDAS-RV).

Table 5
Out-of-sample portfolio performance tests.

Panel (a) Constant expected return [0.81,0.59]			
	GARCH	GARCH-MIDAS-RV	GARCH-MIDAS
GARCH		−1.8849*	−4.8249***
GARCH-MIDAS-RV	1.8849*		−4.9915***
GARCH-MIDAS	4.8249***	4.9915***	
Panel (b) Identical expected return [0.71,0.71]			
	GARCH	GARCH-MIDAS-RV	GARCH-MIDAS
GARCH		−2.7477***	−2.5589**
GARCH-MIDAS-RV	2.7477***		−2.8369***
GARCH-MIDAS	2.5589**	2.8369***	

Notes: The table reports the average of weighted differences between the squared ex post portfolio returns of each two competing models based on the test of Engle and Colacito (2006). The sample is from October 1, 2016 to July 31, 2018. A positive (negative) sign indicates that the row model outperforms (underperforms) the column model. ***, **, * denote significance at the 1%, 5% and 10% levels.

predicted conditional volatility and the true volatility with squared return as a proxy, and MSE is the mean squared error of the two volatilities. The last two rows are the p values of Hansen (2005)'s superior predictive ability (SPA) test statistics with MAE and MSE as loss functions. The null hypothesis is that the benchmark model (GARCH-MIDAS) is not outperformed by any of the other two competing models (GARCH, GARCH-MIDAS-RV).

From Table 4, the GARCH-MIDAS model yields the lowest values of MAE and MSE among the three models, suggesting that the GARCH-MIDAS model gives superior volatility forecast of the CSI 300 Index and CSI 300 futures. Turning to the last two rows of Table 4, the reported high p values of the SPA tests indicate that the GARCH-MIDAS model exhibits at least as high forecasting accuracy as the other two models. As the other two models are only based on daily return information and do not account for monthly macroeconomic factors, it can be inferred that monthly macroeconomic information is useful to predict the volatilities of the CSI 300 Index and CSI 300 futures.

4.6.2. Out-of-sample portfolio performance

Table 5 evaluates the out-of-sample performance of portfolios consisting of the CSI 300 Index and CSI 300 futures. The returns are modeled by GARCH, GARCH-MIDAS-RV and GARCH-MIDAS respectively, and the spot-futures correlation is modeled by Engle (2002)'s dynamic conditional correlation model (DCC). Like Engle and Colacito (2006), we construct portfolios by selecting weights that minimize the portfolio variance subject to a required return while using model-implied covariance matrices as input. Although short sales are generally prohibited in Chinese stock spot market, it is still possible to short the CSI 300 Index by trading some Exchange Trade Funds like Direxion Daily CSI 300 China A Shares Bear 1X Shares. The numbers in the table are the average of the weighted differences between the squared ex post portfolio returns of each two competing models.

Following Asgharian et al. (2016), we focus on two cases of expected return vectors. Panel (a) is [0.81,0.59], the vector of expected spot and futures returns whose ratio close to the ratio of their unconditional means from April 16, 2010 to July 31, 2018 (0.0068 for the CSI 300 Index and 0.0061 for CSI 300 futures). Panel (b) is [0.71,0.71], the vector of identical expected spot and futures returns. We assess the performance of the three models by comparing the squared ex post portfolio returns. A positive (negative) sign indicates that the row model outperforms (underperforms) the column model.

Table 5 shows the rankings of the three models: the GARCH-MIDAS model in this paper is the best, which is followed by GARCH-MIDAS-RV and GARCH. The portfolios based on GARCH-MIDAS and DCC are always significantly preferred to the portfolios based on the other models, as the last row of either Panel (a) or Panel (b) provides significantly positive values. The GARCH-MIDAS model utilizes both monthly economic information and daily return information. Therefore, monthly macroeconomic information does enable us to improve portfolio performance in asset allocations.

5. Robustness analysis

5.1. Alternative economic uncertainty measure

Baker et al. (2016) propose a monthly index of economic policy uncertainty (EPU) based on newspaper coverage frequency, and the EPU index of China is available on the website.[1] We replace the three economic uncertainty factors *CPIvol*, *IPvol* and *CRDvol* by the EPU index and estimate the GARCH-MIDAS models in Table 6. In Panel (a) of Fig. 5 we plot the Beta weights from the value of ω_{EPU}. For comparison reasons, the sample is from April 16, 2010 to September 30, 2016, the same as Table 2.

From Table 6, greater economic policy uncertainty tends to drive up the long-run volatilities of the CSI 300 Index and CSI 300 futures. The results are quite robust as there are no significant changes in other coefficients. The estimates of economic policy uncertainty (θ_{EPU}) for both the stock spot and futures are significantly positive, implying a positive relationship between EPU and market risks.

[1] http://www.policyuncertainty.com/index.html.

Table 6
GARCH-MIDAS model estimates with economic policy uncertainty (EPU).

	Panel (a) CSI			Panel (b) IF		
		Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30
μ	0.0331	0.0346	0.0212	0.0172	0.0124	0.0383
	(0.0317)	(0.0598)	(0.0688)	(0.0515)	(0.0376)	(0.0847)
α	0.0280	0.0364	0.0206	0.055***	0.0451***	0.0579
	(0.1197)	(0.0917)	(0.0291)	(0.0145)	(0.0157)	(0.0741)
β	0.9154***	0.9442***	0.8531*	0.8821***	0.8912***	0.8145***
	(0.0530)	(0.2554)	(0.4498)	(0.0359)	(0.0312)	(0.3112)
c	2.4936***	1.9889***	2.9097***	2.6827***	2.2916***	3.4155***
	(0.9276)	(0.3387)	(0.2231)	(0.4419)	(0.6555)	(0.1861)
θ_{CPI}	1.3092***	1.8607***	1.2987*	1.3486*	1.5562**	1.2574*
	(0.3221)	(0.3869)	(0.7061)	(0.7792)	(0.7326)	(0.7128)
θ_{IP}	−1.2166***	−1.1739*	−3.0227***	−1.5786	−1.6146	−0.2684
	(0.1255)	(0.6900)	(1.0665)	(1.0662)	(1.4622)	(0.6007)
θ_{CRD}	−2.1127**	−1.3897**	−2.4208**	−2.3225***	−2.1727**	−3.9927***
	(0.9466)	(0.5982)	(1.1363)	(0.7200)	(0.8833)	(1.1685)
θ_{EPU}	0.0160***	0.0217**	0.0158***	0.0152***	0.0133	0.0679***
	(0.0053)	(0.0090)	(0.0057)	(0.0056)	(0.0115)	(0.0156)
θ_{PFVM}	3.9092**	3.3778**	4.1481***	8.6965***	6.9458***	9.8300
	(1.5848)	(1.3493)	(1.4554)	(1.2973)	(1.8924)	(28.8956)
ω_{CPI}	6.7779**	4.4347***	7.0245	9.0058***	9.7225***	8.4687***
	(3.0325)	(1.4309)	(10.6328)	(2.3466)	(2.5173)	(2.9277)
ω_{IP}	8.8317*	5.6319*	9.8378***	7.6692	7.1074	8.9644
	(4.5043)	(3.3752)	(3.6837)	(5.4577)	(8.4306)	(6.5155)
ω_{CRD}	6.7200***	6.6451***	7.0902**	7.0259***	7.5814**	6.9750***
	(2.0554)	(1.9110)	(3.1724)	(2.1136)	(3.3747)	(1.9035)
ω_{EPU}	10.7935**	14.6828**	9.5123**	9.7443**	12.3710*	9.3159***
	(5.2696)	(6.1442)	(3.9561)	(4.6054)	(6.3719)	(3.0814)
ω_{PFVM}	16.8839**	15.7668*	24.4719***	23.5373**	29.6670***	17.3955**
	(7.5706)	(8.2594)	(7.0291)	(9.9008)	(10.4270)	(8.5671)
K	48	48	12	48	48	12
logL($\times 10^3$)	−2.8001	−2.1598	−0.6183	−2.9003	−2.2087	−0.6676
AIC($\times 10^3$)	5.6282	4.3476	1.2645	5.8287	4.4454	1.3633
BIC($\times 10^3$)	5.7033	4.4195	1.3173	5.9037	4.5173	1.4161

Notes: The table reports the estimates of GARCH-MIDAS models with economic policy uncertainty (EPU) as uncertainty measure from April 16, 2010 to September 30, 2016, with CSI 300 Index (CSI) in panel (a) and with CSI 300 futures (IF) in panel (b). Brackets below are standard errors. ***, **, * denote significance at the 1%, 5% and 10% levels.

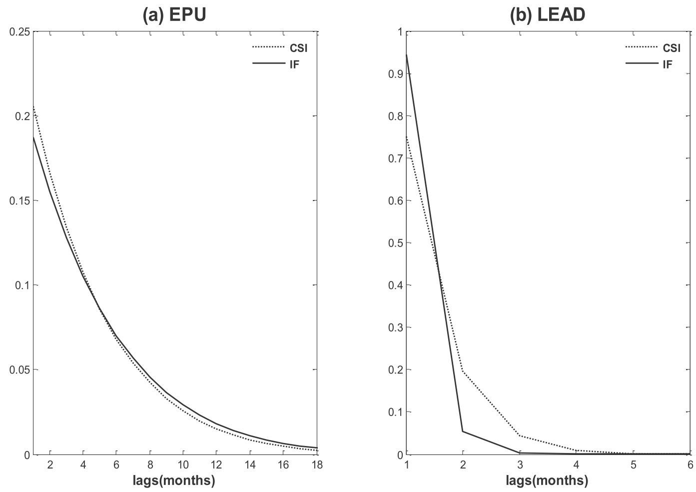
In particular, after the stock market crash, the impact of EPU on the CSI 300 Index volatilities is weakened as θ_{EPU} is lower, while the impact of EPU on CSI 300 futures is strengthened as θ_{EPU} is higher. It is not surprising because the prices of stock index futures reflect the investors' expectations and they are more likely to be affected by economic uncertainty in periods of crisis. Also, Fig. 5 (a) reveals that the influence of EPU on the two markets can last for 18 months as the weights decay to zero at about 18 lags. The impact of EPU is 6 months longer than the impact of *CPIvol*, *IPvol* and *CRDvol* in Fig. 4, indicating that EPU collected from newspapers has more macro-economic information than *CPI*, *IP* and *CRD*.

5.2. Asymmetric structure in GARCH-MIDAS model

Leverage effects are commonly found in equity returns, such as Kao, Wu, and Lee (2012), Asai et al. (2015). The economic intuition is that negative shocks increase the volatility more than positive shocks. To account for the asymmetric effects, we modify the short-run component of the GARCH-MIDAS model into the GJR specification by Glosten, Jagannathan, and Runkle (1993) in equation (Beltratti & Morana, 2006).

$$g_{i,t} = \left(1 - \alpha - \beta - \frac{\gamma}{2}\right) + [\alpha + \gamma I(r_{i-1,t} < 0)]\frac{(r_{i-1,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t}. \tag{6}$$

$I(\cdot)$ is an indicator function. A positive γ signifies the leverage effects, and the following conditions must be satisfied: $\alpha > 0$, $\alpha + \gamma > 0$, $\beta > 0$, $\alpha + \beta + \gamma/2 < 1$.



Notes: Panel (a) depicts the impacts of monthly economic policy uncertainty (EPU) on the long-run volatilities of CSI 300 Index (CSI) and CSI 300 futures (IF) based on the results in Table 6. Panel (b) depicts the impacts of monthly leading economic indicator (LEAD) on the long-run volatilities of CSI 300 Index (CSI) and CSI 300 futures (IF) based on the results in Table 8. The sample is from April 16, 2010 to September 30, 2016.

Fig. 5. Impacts of monthly economic policy uncertainty and leading economic indicator on the volatilities of CSI 300 Index and CSI 300 futures

Notes: Panel (a) depicts the impacts of monthly economic policy uncertainty (EPU) on the long-run volatilities of CSI 300 Index (CSI) and CSI 300 futures (IF) based on the results in Table 6. Panel (b) depicts the impacts of monthly leading economic indicator (LEAD) on the long-run volatilities of CSI 300 Index (CSI) and CSI 300 futures (IF) based on the results in Table 8. The sample is from April 16, 2010 to September 30, 2016.

Table 7 presents the results of the asymmetric GARCH-MIDAS models with the same sample as Table 2. The results are quite robust when asymmetric structure is considered. Leverage effects are present in both the CSI 300 Index and CSI 300 futures as the values of γ are positive. It indicates that bad news leads to higher volatility than good news in both stock spot and futures markets. Furthermore, the estimates of γ are insignificant in sample 1 but significant and positive in sample 2, implying that most of the leverage effects come from the 2015 crisis period. It explains why our results differ from Yeh and Lee (2000) and Hou (2013), who use the data in the 1990s and 2000s and find that greater impact of good news on volatility than bad news in Chinese stock market.

5.3. Two-sided extension of GARCH-MIDAS model

Engle et al. (2013) suggest that the performance of GARCH-MIDAS model can be improved by including the future values of macroeconomic variables when we anticipate market volatility. To examine the impact of market expectation on volatility, we revise the long-run volatility of GARCH-MIDAS model in equation (Asgharian et al., 2013) into equation (Bohl et al., 2015) with two-sided filters as in Conrad and Loch (2015) and Asgharian et al. (2016).

$$\log\tau_t = c + \sum_{q=1}^{Q_{LAG}}\left[\theta_q^{LAG}\sum_{k=1}^{K_{LAG}}\varphi_k\left(\omega_q^{LAG}\right)X_{q,t-k}\right] + \sum_{q=1}^{Q_{LEAD}}\left[\theta_q^{LEAD}\sum_{k=1}^{K_{LEAD}}\varphi_k\left(\omega_q^{LEAD}\right)X_{q,t+k-1|t}\right]. \quad (7)$$

The long-run volatility τ_t is not only related to Q_{LAG} historical economic variables, but also related to Q_{LEAD} forecasted economic variables. Since China has no Survey of Professional Forecasters (SPF) database as the U.S., we consider the leading economic indicator in China as a proxy for market expectations. The leading economic indicator first developed by the NBER researchers is a combination of several major financial and economic indicators and it has been shown to provide a better forecast of business cycle behavior in Auerbach (1982). The monthly Chinese leading economic indicator is available at the Macroeconomic Monitoring and Forecasting System in China Economic Network.[2]

In Table 8, we include 7 historical economic variables ($Q_{LAG} = 7$) that are already in Tables 2 and 1 leading economic indicator ($Q_{LEAD} = 1$). The lag of historical observations K_{LAG} is 48 and the lag of future observations K_{LEAD} is 12, which are determined by simulations to obtain the highest maximum log-likelihood values. Besides, In Panel (b) of Fig. 5 we plot the Beta weights from the value of ω_{LEAD}. Again, for comparison reasons, the sample is from April 16, 2010 to September 30, 2016.

Table 8 shows that the long-run volatilities of the CSI 300 Index and CSI 300 futures are negatively related to the leading economic indicator. The results of other economic variables are robust when two-sided filters are considered. In either Panel (a) or (b), θ_{LEAD} is significantly negative, meaning that high expectations about future business conditions are associated with declines in long-run

[2] http://macro.cei.cn/web/Page/Default.aspx.

Table 7
Asymmetric GARCH-MIDAS model estimates.

	Panel (a) CSI			Panel (b) IF		
		Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30
μ	0.0137	0.0398	0.0102	0.0149	0.0298	0.0041
	(0.1256)	(0.0441)	(0.0675)	(0.0333)	(0.0926)	(0.0144)
α	0.0269	0.0203	0.0283	0.0191	0.0332	0.0136**
	(0.7406)	(0.1295)	(0.2251)	(0.0211)	(0.0267)	(0.0063)
β	0.9262***	0.9266***	0.8500***	0.8876***	0.9049***	0.8185***
	(0.0294)	(0.0359)	(0.0343)	(0.0337)	(0.0311)	(0.0344)
γ	0.0349**	0.0082	0.0598***	0.0520**	0.0178	0.0635***
	(0.0163)	(0.0131)	(0.0124)	(0.0264)	(0.0414)	(0.0242)
c	1.9062***	1.8437***	2.8203***	2.1037***	1.9809***	3.3331***
	(0.5673)	(0.5014)	(0.8126)	(0.5030)	(0.5478)	(0.7668)
θ_{CPI}	1.0381*	3.0277	0.9672***	1.2261***	1.3372**	0.5799***
	(0.5834)	(2.1664)	(0.3675)	(0.4704)	(0.5644)	(0.1769)
θ_{IP}	−3.5796**	−0.6476	−6.1578***	−1.6135	−0.4781***	−3.3765
	(1.7067)	(0.4013)	(1.5554)	(1.6423)	(0.1677)	(3.3160)
θ_{CRD}	−4.6712***	−1.0007**	−5.6395***	−4.5001***	−2.0318*	−8.2703***
	(1.4001)	(0.4704)	(1.8840)	(1.5128)	(1.1388)	(1.6109)
θ_{CPIvol}	0.0309*	0.0273*	0.0358	0.0363**	0.0467***	0.0342**
	(0.0180)	(0.0149)	(0.0327)	(0.0154)	(0.0153)	(0.0172)
θ_{IPvol}	0.4335*	0.4164***	0.4373*	0.1010*	0.1213*	0.0967
	(0.2319)	(0.1589)	(0.2648)	(0.0528)	(0.0709)	(0.0854)
θ_{CRDvol}	1.2694**	3.0372***	1.2113**	1.5017***	1.7289***	1.4793**
	(0.5960)	(1.1725)	(0.4866)	(0.5689)	(0.6461)	(0.7441)
θ_{PFVM}	5.8570***	5.1547***	6.8460***	7.7923**	7.0025**	9.8379
	(1.7548)	(1.4008)	(2.2922)	(3.3531)	(2.7488)	(8.8075)
ω_{CPI}	6.4401*	6.6663	5.7148*	7.3983***	6.0661***	9.0986**
	(3.3181)	(5.3782)	(2.9804)	(1.2039)	(0.5919)	(3.9178)
ω_{IP}	7.8039***	3.5851	9.0826***	4.8099	3.8019	5.8558
	(2.7953)	(2.8149)	(2.8655)	(4.2552)	(4.5815)	(4.8132)
ω_{CRD}	8.0195***	8.0768***	7.5384***	6.3583***	7.7620***	9.5669**
	(2.9843)	(2.3975)	(2.1001)	(1.9317)	(2.1632)	(4.0505)
ω_{CPIvol}	13.0631**	12.1100***	14.7444	9.2519**	9.1951***	9.9496**
	(6.4126)	(4.5658)	(10.5666)	(4.6149)	(3.1026)	(4.5830)
ω_{IPvol}	8.4639	8.0387	8.5927	18.3867***	19.8870***	16.5417***
	(8.6209)	(6.0269)	(9.4003)	(5.2967)	(5.6670)	(4.1168)
ω_{CRDvol}	14.0070**	11.1424*	18.4291***	16.0090***	13.1630**	16.2461***
	(5.8717)	(6.3583)	(6.4064)	(6.0991)	(5.4584)	(5.2745)
ω_{PFVM}	17.3346***	12.5600**	24.8688***	20.3634***	24.7153***	12.5434
	(6.0724)	(6.3408)	(9.3475)	(7.8100)	(7.6165)	(9.5854)
K	48	48	12	48	48	12
logL($\times 10^3$)	−2.7841	−2.1530	−0.6032	−2.8926	−2.1955	−0.6612
AIC($\times 10^3$)	5.6062	4.3439	1.2445	5.8232	4.4290	1.3604
BIC($\times 10^3$)	5.7081	4.4415	1.3161	5.9251	4.5265	1.4320

Notes: The table reports the estimates of asymmetric GARCH-MIDAS models from April 16, 2010 to September 30, 2016, with CSI 300 Index (CSI) in panel (a) and with CSI 300 futures (IF) in panel (b). Brackets below are standard errors. ***, **, * denote significance at the 1%, 5% and 10% levels.

volatility. In particular, CSI 300 futures have a higher θ_{LEAD} (in absolute value) than the CSI 300 Index, implying that the futures market is more likely to be affected by market expectations. In addition, after the 2015 market crash, the estimate of θ_{LEAD} decreases (in absolute value) for the CSI 300 Index, and the estimate of θ_{LEAD} becomes insignificant for CSI 300 futures. It is concluded that market expectations are less powerful in explaining market volatilities in crisis period than in tranquil period. In Fig. 5(b) the weights of the leading economic indicator decay to zero after 3–5 months. It is inferred that the impact of the leading economic indicator only lasts for 3–5 months, which is less persistent than the impact of economic fundamentals, economic uncertainty and speculation.

5.4. Short-term impact of economic variables in GARCH-MIDAS model

Some economic variables related to stock volatility can be observed at higher frequency than monthly, such as the interest rates. So it is interesting to see whether these daily economic variables can explain the long-run volatility. It is also necessary to check the robustness of our results when daily economic factors are considered. Following Gong, Chen, and Zheng (2016), we revise equation

Table 8
GARCH-MIDAS model estimates with two-sided filters.

	Panel (a) CSI			Panel (b) IF		
		Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30
μ	0.0476**	0.0423	0.0542**	0.0398	0.0187	0.0537
	(0.0233)	(0.0333)	(0.0211)	(0.0259)	(0.0423)	(0.0363)
α	0.0362***	0.0565***	0.0252	0.0295*	0.0296*	0.0282
	(0.0128)	(0.0115)	(0.0347)	(0.0159)	(0.0159)	(0.0343)
β	0.8836***	0.8925***	0.7418***	0.8647***	0.8789***	0.7615***
	(0.0345)	(0.1051)	(0.1474)	(0.0319)	(0.0437)	(0.0721)
c	4.6666***	2.4035***	5.4572***	4.1122***	3.9464***	6.8888***
	(0.7400)	(0.7512)	(0.5607)	(1.3444)	(0.9025)	(2.5111)
θ_{CPI}	10.5653**	13.8767**	9.9224***	1.4952**	2.0124***	1.3855
	(4.8907)	(6.2083)	(1.9470)	(0.7358)	(0.7544)	(1.1549)
θ_{IP}	−3.8357**	−3.4415*	−5.4903**	(4.8626)	(5.0216)	(2.2453)
	(1.7377)	(1.9572)	(2.4292)	(4.1568)	(16.5957)	(33.1037)
θ_{CRD}	−3.7782***	−1.2556***	−7.1009**	−1.9424***	−1.4181**	−4.7854***
	(1.0304)	(0.3789)	(3.4406)	(0.6065)	(0.5508)	(1.0337)
θ_{CPIvol}	0.0886*	0.2937**	(0.1859)	0.0624*	0.0670	0.0457**
	(0.0468)	(0.1218)	(0.1676)	(0.0372)	(0.0704)	(0.0186)
θ_{IPvol}	0.1442	0.7925	0.1206*	0.4253***	0.5692***	0.2951***
	(0.3422)	(1.1872)	(0.0627)	(0.0856)	(0.1250)	(0.0682)
θ_{CRDvol}	1.1304**	2.0224**	1.3380**	1.0951	0.7735***	1.2106
	(0.5090)	(0.8101)	(0.6257)	(2.3872)	(0.2619)	(1.3424)
θ_{PFVM}	5.8602***	4.7435***	7.8662***	5.5908***	7.3414***	4.1421***
	(1.5062)	(1.5308)	(0.8367)	(1.4182)	(1.2872)	(1.0430)
θ_{LEAD}	−0.0288***	−0.0341***	−0.0272***	−0.0589**	−0.0201**	−0.1112
	(0.0057)	(0.0069)	(0.0055)	(0.0254)	(0.0079)	(0.1089)
ω_{CPI}	7.6871***	6.2760***	8.3217***	6.7571**	6.0511**	7.1344**
	(2.9711)	(2.0176)	(2.6942)	(2.9712)	(2.7163)	(3.1654)
ω_{IP}	7.2329***	6.3949***	8.2132**	7.7247	6.7033	9.6130
	(1.0016)	(2.2030)	(3.5971)	(9.0200)	(9.5848)	(11.3395)
ω_{CRD}	6.8244***	7.0146***	6.7503***	5.3531***	6.5596***	4.8904***
	(2.5134)	(1.6415)	(1.8768)	(1.3809)	(1.1092)	(1.1551)
ω_{CPIvol}	14.9894**	13.2105***	18.1071	19.5298*	12.8841*	20.2075***
	(5.8190)	(1.5553)	(12.1052)	(10.7455)	(7.7984)	(7.6046)
ω_{IPvol}	10.0962	14.4502	5.6383***	19.9795**	16.6443**	26.5669***
	(10.4540)	(25.6544)	(1.1045)	(8.9905)	(8.3797)	(7.9836)
ω_{CRDvol}	16.2437***	11.4063***	18.8658***	14.1524**	11.2536**	15.9717***
	(2.1131)	(2.7884)	(2.3854)	(6.5560)	(5.2976)	(4.5696)
ω_{PFVM}	14.9536***	13.9139**	19.8843***	14.5625***	24.646***	11.0823
	(5.5071)	(5.8295)	(5.9916)	(4.6350)	(8.3375)	(7.1686)
ω_{LEAD}	15.0155***	15.1041***	15.0150***	31.1562***	15.0179***	83.3762***
	(1.8934)	(1.0782)	(0.9609)	(9.8549)	(4.9993)	(25.9774)
K_{LAG}	48	48	12	48	48	12
K_{LEAD}	12	12	12	12	12	12
logL($\times 10^3$)	−2.7516	−2.1249	−0.5904	−2.8848	−2.1742	−0.6175
AIC($\times 10^3$)	5.5432	4.2898	1.2208	5.8096	4.3884	1.2750
BIC($\times 10^3$)	5.6504	4.3924	1.2962	5.9168	4.4910	1.3504

Notes: The table reports the estimates of GARCH-MIDAS model with two-sided filters from April 16, 2010 to September 30, 2016, with CSI 300 Index (CSI) in panel (a) and with CSI 300 futures (IF) in panel (b). The leading economic indicator in China is used to construct the two-sided filters. Brackets below are standard errors. ***, **, * denote significance at the 1%, 5% and 10% levels.

(Asgharian et al., 2016) in GARCH-MIDAS model into equation (Caginalp & DeSantis, 2017). In this case, equation (Caginalp & DeSantis, 2017) incorporates P daily lagged economic variables into the short-run component of volatility, and equation (Asgharian et al., 2013) incorporates Q monthly lagged economic variables into the long-run component of volatility. Due to the availability of daily data, here we only consider the daily interest rates (IR) measured by Shanghai Interbank Offered Rates (SHIBOR) from April 16, 2010 to September 30, 2016, the same sample as Table 2. SHIBOR is downloaded from Wind Financial Terminal.

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t}-\mu)^2}{\tau_t} + \beta g_{i-1,t} + \sum_{p=1}^{P}\theta_p X_{p,i-1,t}, \quad p=1,\cdots,P. \tag{8}$$

From Table 9, daily SHIBOR seems to be a poor predictor of the CSI 300 spot and futures volatilities as the estimates of θ_{IR} are insignificant in Panels (a) and (b). It should also be noted that when daily interest rates are added, the estimates of θ_{CRD} are not as significant as those in Table 2, in particular before the stock market crash. It is concluded that credit policy and interest rates may share some identical information about monetary policy, which causes both θ_{IR} and θ_{CRD} to be insignificant (or less significant). In comparison with Table 2, the values of information criteria are not necessarily lower in Table 9. It means monthly credit growth rates alone are good enough at explaining stock index and futures volatilities. Last, the estimates of other monthly economic factors are quite similar to those in Table 2, which confirms the robustness of our results.

5.5. Extension of the stock index sample period

All the in-sample results above are based upon the data from April 16, 2010 to September 30, 2016. The results using the six-year

Table 9
GARCH-MIDAS model estimates with daily interest rates (IR) as explanatory variables.

	Panel (a) CSI			Panel (b) IF		
	:	Sample 1	Sample 2		Sample 1	Sample 2
	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30	2010/4/16–2016/9/30	2010/4/16–2015/6/14	2015/6/15–2016/9/30
μ	0.0225	0.0342	0.0166***	0.0075	0.0104	0.0041
	(0.0185)	(0.0255)	(0.0061)	(0.0307)	(0.0272)	(0.0375)
α	0.0207**	0.0363**	0.0190	0.0594***	0.0383**	0.0736
	(0.0089)	(0.0172)	(0.0511)	(0.0169)	(0.0184)	(0.5897)
β	0.8742***	0.9315***	0.8508***	0.8734***	0.8889***	0.7834***
	(0.1186)	(0.1996)	(0.1928)	(0.1115)	(0.1019)	(0.1668)
c	1.7664***	1.2481**	1.9320***	2.0257***	1.4180**	2.5780***
	(0.2065)	(0.5504)	(0.7440)	(0.6131)	(0.5963)	(0.5585)
θ_{IR}	0.0125	0.0084	1.1859	0.0174	0.0095	0.9403
	(0.0198)	(0.0223)	(0.8256)	(0.0502)	(0.0124)	(0.5819)
θ_{CPI}	1.5813*	1.6464**	1.1009	1.7598***	2.6013***	1.2567*
	(0.8756)	(0.8169)	(1.0599)	(0.6368)	(0.8035)	(0.6973)
θ_{IP}	−2.448***	−1.7735***	−4.4432**	−1.8285	−0.8976	−1.9019
	(0.8379)	(0.5201)	(2.1485)	(1.8447)	(0.5864)	(1.8222)
θ_{CRD}	−3.4919**	−1.2867	−5.4062***	−3.8678**	−0.8811	−6.6660***
	(1.4005)	(2.2189)	(1.7834)	(1.8126)	(1.0300)	(2.4798)
θ_{CPIvol}	0.0225*	0.0159*	0.0231	0.0490**	0.0550**	0.0424*
	(1.4005)	(2.2189)	(1.7834)	(1.8126)	(1.0300)	(2.4798)
θ_{IPvol}	1.4580	0.2600	2.9165	0.3141	0.1604*	0.3567
	(1.0016)	(0.5239)	(2.1671)	(0.3219)	(0.0967)	(0.2218)
θ_{CRDvol}	1.3524**	2.9798**	1.2269**	1.5318*	1.2153*	1.5529*
	(0.6299)	(1.2986)	(0.5313)	(0.8478)	(0.7070)	(0.8577)
θ_{PFVM}	6.8716**	4.4018**	7.7747***	4.9338**	4.2865**	8.3419*
	(3.2144)	(2.0885)	(2.4787)	(2.3677)	(1.8713)	(4.8654)
ω_{CPI}	7.5114**	6.7816**	8.1089**	6.6391***	8.2050***	4.8448*
	(3.6992)	(3.3800)	(3.7300)	(2.2742)	(3.1076)	(2.6079)
ω_{IP}	9.7882***	3.7245	10.6306***	5.6923	8.3351*	4.6663
	(3.3367)	(2.3013)	(3.9854)	(3.6781)	(4.8480)	(3.8132)
ω_{CRD}	6.7007***	8.0080***	6.1585**	6.3705**	5.3430**	8.3088***
	(2.5507)	(2.0992)	(2.7685)	(3.0634)	(2.6901)	(2.7377)
ω_{CPIvol}	14.4143**	13.8800**	15.7867*	14.0975**	10.8102**	18.3622***
	(6.7404)	(6.3229)	(8.3444)	(5.8022)	(5.2693)	(6.3337)
ω_{IPvol}	13.1133	18.7769	15.8197	16.3089**	18.7289***	10.0984
	(12.2867)	(13.3448)	(15.3664)	(6.7405)	(5.7113)	(6.5703)
ω_{CRDvol}	13.3044**	10.6459**	15.6176***	14.2405***	15.5777***	11.8751***
	−5.3407	−4.8050	−4.5148	−3.6087	−2.8368	−3.2524
ω_{PFVM}	15.2305**	13.6111**	17.7364**	27.4910***	30.4041***	10.0106**
	(6.6896)	(5.5133)	(7.3935)	(8.0843)	(7.5872)	(4.3059)
K	48	48	12	48	48	12
logL($\times 10^3$)	−2.7874	−2.1509	−0.6014	−2.8899	−2.1988	−0.6578
AIC($\times 10^3$)	5.6128	4.3399	1.2407	5.8178	4.4356	1.3537
BIC($\times 10^3$)	5.7147	4.4374	1.3123	5.9197	4.5331	1.4253

Notes: The table reports the estimates of GARCH-MIDAS model with daily interest rates (IR) as explanatory variables from April 16, 2010 to September 30, 2016, with CSI 300 Index (CSI) in panel (a) and with CSI 300 futures (IF) in panel (b). Brackets below are standard errors. ***, **, * denote significance at the 1%, 5% and 10% levels.

sample may not be convincing enough as the first four-year sample is used in the MIDAS filter. It is known that the CSI 300 Index and CSI 300 futures are not available for longer periods. So we investigate the volatilities of two other stock indices with longer history: Shanghai Composite Index and Shenzhen Component Index. The sample is extended to around 17 years: from July 1, 1999 to September 30, 2016. It starts in July 1999 because the industrial production data is available after July 1998 and the first one-year data is used for seasonal adjustment. The data are from CSMAR Solution provided by GTA Finance and Education Group and Wind Financial Terminal.

Table 10 provides quite similar results to Panel (a) of Table 2, which confirms the robustness of our results. But it is worth mentioning that the estimates of θ_{CPI}、 θ_{IP} and θ_{CRD} (in absolute value) are much larger in Table 10 than in Table 2(a). It means that the three economic fundamentals play more important roles in the long-run volatility when the sample is extended. In other words, the stock spot market is more closely linked with economic fundamentals in the 2000s than in the 2010s. Between Shanghai and Shenzhen markets, θ_{CPI} and θ_{IP} are higher (in absolute value) in Shanghai while θ_{CRD} is higher (in absolute value) in Shenzhen. It tells us that Shanghai stock market is more sensitive to the changes in price level and real economic growth, while Shenzhen stock market is more sensitive to the changes in credit policies.

Table 10
GARCH-MIDAS model estimates with longer sample periods.

	Panel (a) Shanghai Composite Index			Panel (b) Shenzhen Component Index		
		Sample 1	Sample 2		Sample 1	Sample 2
	1999/7/1–2016/9/30	1999/7/1–2015/6/14	2015/6/15–2016/9/30	1999/7/1–2016/9/30	1999/7/1–2015/6/14	2015/6/15–2016/9/30
μ	0.0308	0.0347	0.0070	0.0171	0.0218	0.0034
	(0.0291)	(0.0317)	(1.1727)	(0.0426)	(0.0305)	(0.0042)
α	0.0773***	0.0810***	0.0712	0.0732***	0.0777***	0.0644
	(0.0129)	(0.0162)	(0.4927)	(0.0111)	(0.0125)	(0.3238)
β	0.8543***	0.8643***	0.8083**	0.8026***	0.9073***	0.8053***
	(0.0190)	(0.0180)	(0.3923)	(0.0149)	(0.0174)	(0.0005)
c	−11.5938***	−12.8069***	2.7600***	−1.7962***	−2.1431***	2.7780***
	(3.7868)	(3.6552)	(0.6677)	(0.6392)	(0.5555)	(0.2097)
θ_{CPI}	12.6462***	13.7684***	6.6144**	4.1868**	2.2004**	10.6965**
	(4.3295)	(3.8159)	(2.7267)	(2.0386)	(0.9931)	(4.5085)
θ_{IP}	−10.6599***	−9.3829**	−13.3565***	−8.0492***	−2.4275***	−9.6443***
	(3.9503)	(4.4048)	(3.3670)	(1.7459)	(0.7241)	(3.5650)
θ_{CRD}	−11.0067**	−10.0449*	−32.6232**	−28.5560***	−8.4097***	−32.0584**
	(4.6694)	(5.9763)	(15.9609)	(3.4836)	(2.9291)	(12.7937)
θ_{CPIvol}	1.1639	2.0405	−2.9405	0.5421	0.3626**	0.8614
	(1.5085)	(2.3288)	(5.6065)	(0.3613)	(0.1759)	(0.9496)
θ_{IPvol}	0.8037	0.4547	1.0365	0.3620	0.7272**	0.1324
	(1.8823)	(0.4045)	(1.1760)	(0.4085)	(0.3339)	(0.8120)
θ_{CRDvol}	3.3145***	4.0102*	1.7051***	1.6216**	1.8629***	1.3375**
	(1.0130)	(2.1744)	(0.4829)	(0.7035)	(0.6427)	(0.5793)
θ_{PFVM}	1.7591**	1.4293	2.5086***	3.1220**	2.0358**	4.7685**
	(0.8484)	(1.5551)	(0.6897)	(1.3271)	(0.8589)	(2.4198)
ω_{CPI}	6.4273***	6.6166***	10.8787***	6.7154**	7.9392*	5.8357***
	(1.1996)	(1.1716)	(2.3482)	(2.7373)	(4.1582)	(2.0611)
ω_{IP}	6.8806*	6.3452*	7.8496**	6.2172***	6.5605***	4.0087**
	(3.5974)	(3.8039)	(3.3611)	(1.6524)	(1.5752)	(2.0320)
ω_{CRD}	6.1457***	5.6282*	7.5673***	6.5065***	7.3448**	5.9528***
	(2.2005)	(3.0779)	(2.4110)	(1.1650)	(2.9595)	(0.6732)
ω_{CPIvol}	6.6030	3.3014*	9.9917	8.4160*	7.4719	9.3927**
	(4.7566)	(1.7039)	(6.5143)	(4.6230)	(7.1268)	(4.6223)
ω_{IPvol}	7.6732	7.7831**	3.4552	13.2982	11.0112	18.6331***
	(5.0702)	(3.6212)	(6.6488)	(25.4330)	(19.1280)	(7.1290)
ω_{CRDvol}	10.4708***	9.4417***	10.9097***	10.7663**	9.0091**	13.0031**
	(2.2288)	(2.8618)	(2.4365)	(4.9121)	(4.4660)	(5.6101)
ω_{PFVM}	13.4667***	10.6925**	16.0456***	16.0759***	11.6103***	20.0210***
	(5.1223)	(4.8641)	(5.6630)	(4.6394)	(4.0097)	(5.7806)
K	48	48	12	48	48	12
logL($\times 10^3$)	−2.4620	−1.8147	−0.6096	−2.7132	−1.8870	−0.6126
AIC($\times 10^3$)	4.9601	3.6654	1.2553	5.4624	3.8100	1.2611
BIC($\times 10^3$)	5.0742	3.7781	1.3231	5.5765	3.9227	1.3290

Notes: The table reports the estimates of GARCH-MIDAS model from July 1, 1999 to September 30, 2016, with Shanghai Composite Index in panel (a) and with Shenzhen Component Index in panel (b). Brackets below are standard errors. ***, **, * denote significance at the 1%, 5% and 10% levels.

6. Conclusion

To achieve a deeper understanding of the Chinese stock market, we study the economic sources of CSI 300 spot and futures volatilities. A GARCH-MIDAS model is utilized, as the spot and futures prices are observed daily and the economic factors are observed on a monthly basis. To the best of our knowledge, this is the first paper to simultaneously examine the three economic sources in Chinese CSI 300 spot and futures markets.

The findings yield a number of specific conclusions. First, the risks of the CSI 300 Index tend to increase with higher inflation, lower economic growth, tighter credit conditions and more variant credit policies, while the risks of CSI 300 futures tend to increase with higher inflation, tighter credit conditions, more variant inflation rates and credit policies. Second, the effects of economic fundamentals are greater and more prolonged than the effects of economic uncertainty and speculative trading. Hence, investors are advised to pay heed to the changes in price levels, economic development and credit policies when managing their portfolio risks. Lastly but most importantly, when futures trading was highly restricted after the 2015 stock market crash, speculation no longer contributed to the risks of CSI 300 futures. Therefore, it is time for regulatory sectors to ease trading restrictions and resume index futures trading in a step-by-step manner.

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The economic sources of China's CSI 300 spot and futures volatilities before and after the 2015 stock market crisis.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2019.05.017.

References

Asai, M., Caporin, M., & McAleer, M. (2015). Forecasting Value-at-Risk using block structure multivariate stochastic volatility models. *International Review of Economics & Finance, 40*, 40–50.
Asgharian, H., Christiansen, C., & Hou, A. J. (2016). Macro-finance determinants of the long-run stock–bond correlation: The DCC-MIDAS specification. *Journal of Financial Econometrics, 14*(3), 617–642.
Asgharian, H., Hou, A. J., & Javed, F. (2013). The importance of the macroeconomic variables in forecasting stock return variance: A GARCH-MIDAS approach. *Journal of Forecasting, 32*(7), 600–612.
Auerbach, A. J. (1982). The Index of leading indicators:" Measurement without theory," Thirty-five years later. *The Review of Economics and Statistics*, 589–595.
Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *Quarterly Journal of Economics, 131*(4), 1593–1636.
Beltratti, A., & Morana, C. (2006). Breaks and persistency: Macroeconomic causes of stock market volatility. *Journal of Econometrics, 131*(1), 151–177.
Bohl, M. T., Diesteldorf, J., & Siklos, P. L. (2015). The effect of index futures trading on volatility: Three markets for Chinese stocks. *China Economic Review, 34*, 207–224.
Caginalp, G., & DeSantis, M. (2017). Does price efficiency increase with trading volume? Evidence of nonlinearity and power laws in ETFs. *Physica A: Statistical Mechanics and Its Applications, 467*, 436–452.
Chen, G. M., Firth, M., & Rui, O. M. (2001). The dynamic relation between stock returns, trading volume, and volatility. *Financial Review, 36*(3), 153–174.
Colacito, R., Engle, R. F., & Ghysels, E. (2011). A component model for dynamic correlations. *Journal of Econometrics, 164*(1), 45–59.
Conrad, C., & Loch, K. (2015). Anticipating long-term stock market volatility. *Journal of Applied Econometrics, 30*(7), 1090–1114.
Corradi, V., Distaso, W., & Mele, A. (2013). Macroeconomic determinants of stock volatility and volatility premiums. *Journal of Monetary Economics, 60*(2), 203–220.
Darrat, A. F., & Rahman, S. (1995). Has futures trading activity caused stock price volatility? *Journal of Futures Markets, 15*(5), 537–557.
Diebold, F. X., & Yilmaz, K. (2008). Macroeconomic volatility and stock market volatility, worldwide. In *NBER working paper series*. New York: National Bureau of Economic Research.
Engle, R. (2002). Dynamic conditional correlation [J]. *Journal of Business & Economic Statistics, 20*(3), 339–350.
Engle, R., & Colacito, R. (2006). Testing and valuing dynamic correlations for asset allocation. *Journal of Business & Economic Statistics, 24*(2), 238–253.
Engle, R. F., Ghysels, E., & Sohn, B. (2013). Stock market volatility and macroeconomic fundamentals. *The Review of Economics and Statistics, 95*(3), 776–797.
Engle, R. F., & Rangel, J. G. (2008). The spline-GARCH model for low-frequency volatility and its global macroeconomic causes. *Review of Financial Studies, 21*(3), 1187–1222.
Floros, C., & Salvador, E. (2016). Volatility, trading volume and open interest in futures markets. *International Journal of Managerial Finance, 12*(5), 629–653.
Gallant, A. R., Rossi, P. E., & Tauchen, G. (1992). Stock prices and volume. *Review of Financial Studies, 5*(2), 199–242.
Gao, B., & Yang, C. (2017). Forecasting stock index futures returns with mixed-frequency sentiment. *International Review of Economics & Finance, 49*, 69–83.
Ghysels, E., & Seon, J. (2005). The asian financial crisis: The role of derivative securities trading and foreign investors in korea. *Journal of International Money and Finance, 24*(4), 607–630.
Girardin, E., & Joyeux, R. (2013). Macro fundamentals as a source of stock market volatility in China: A GARCH-MIDAS approach. *Economic Modelling, 34*, 59–68.
Girardin, E., & Liu, Z. (2005). Bank credit and seasonal anomalies in China's stock markets. *China Economic Review, 16*(4), 465–483.
Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance, 48*(5), 1779–1801.
Gong, Y., Chen, Q., & Zheng, X. (2016). What really determines the co-movement of stock and bond markets: From the perspective of copula-MIDAS models (In Chinese). *China Economic Quarterly, 15*(3), 1205–1224.
Gwilym, O. A., McMillan, D., & Speight, A. (1999). The intraday relationship between volume and volatility in LIFFE futures markets. *Applied Financial Economics, 9*(6), 593–604.
Han, Q., & Liang, J. (2017). Index futures trading restrictions and spot market quality: Evidence from the recent Chinese stock market crash. *Journal of Futures Markets, 37*(4), 411–428.
Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business & Economic Statistics, 23*(4), 365–380.
Hou, A. J. (2013). Asymmetry effects in Chinese stock markets volatility: A generalized additive nonparametric approach. *Journal of International Financial Markets, Institutions & Money, 23*, 12–32.
Hou, A., & Suardi, S. (2012). A nonparametric GARCH model of crude oil price return volatility. *Energy Economics, 34*(2), 618–626.

Kao, L. J., Wu, P. C., & Lee, C. F. (2012). Time-changed GARCH versus the GARJI model for prediction of extreme news events: An empirical study. *International Review of Economics & Finance, 21*(1), 115–129.

Kleidon, A. W., & Whaley, R. E. (1992). One market? Stocks, futures, and options during october 1987. *The Journal of Finance, 47*(3), 851–877.

Lamoureux, C. G., & Lastrapes, W. D. (1990). Heteroskedasticity in stock return data: Volume versus GARCH effects. *The Journal of Finance, 45*(1), 221–229.

Mei, J., Scheinkman, J., & Xiong, W. (2009). Speculative trading and stock prices: Evidence from Chinese AB share premia. *Annals of Economics and Finance, 10*(2), 225–255.

Morelli, D. (2002). The relationship between conditional stock market volatility and conditional macroeconomic volatility: Empirical evidence based on UK data. *International Review of Financial Analysis, 11*(1), 101–110.

Paye, B. S. (2012). 'Déjà vol': Predictive regressions for aggregate stock market volatility using macroeconomic variables. *Journal of Financial Economics, 106*(3), 527–546.

Pierdzioch, C., Döpke, J., & Hartmann, D. (2008). Forecasting stock market volatility with macroeconomic variables in real time. *Journal of Economics and Business, 60*(3), 256–276.

Schwert, G. W. (1989). Why does stock market volatility change over time? *The Journal of Finance, 44*(5), 1115–1153.

Wang, G. J., Jiang, Z. Q., Lin, M., Xie, C., & Stanley, H. E. (2018). Interconnectedness and systemic risk of China's financial institutions. *Emerging Markets Review, 35*, 1–18.

Wang, G. J., & Xie, C. (2013). Cross-correlations between the CSI 300 spot and futures markets. *Nonlinear Dynamics, 73*(3), 1687–1696.

Wang, G. J., Xie, C., Jiang, Z. Q., & Stanley, H. E. (2016). Extreme risk spillover effects in world gold markets and the global financial crisis. *International Review of Economics & Finance, 46*, 55–77.

Wen, F., & Yang, X. (2009). Empirical study on relationship between persistence-free trading volume and stock return volatility. *Global Finance Journal, 20*(2), 119–127.

Yang, L., Cai, X. J., & Hamori, S. (2018). What determines the long-term correlation between oil prices and exchange rates? *The North American Journal of Economics and Finance, 44*, 140–152.

Yang, J., Yang, Z., & Zhou, Y. (2012). Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China. *Journal of Futures Markets, 32*(2), 99–121.

Yeh, Y. H., & Lee, T. S. (2000). The interaction and volatility asymmetry of unexpected returns in the greater China stock markets. *Global Finance Journal, 11*(1–2), 129–149.