Journal of Futures Markets

Does Index Futures Trading Reduce Volatility in the Chinese Stock Market? A Panel Data Evaluation Approach

Journal:	*Journal of Futures Markets*
Manuscript ID:	Futures-11-4328.R2
Wiley - Manuscript type:	Research Article
Key Words:	Stock index futures, Spot market volatility, Panel data, Chinese stock market

Does Index Futures Trading Reduce Volatility in the Chinese Stock Market? A Panel Data Evaluation Approach

Haiqiang Chen, Qian Han,[1] Yingxing Li, Kai Wu

The Wang Yanan Institute for Studies in Economics,
MOE Key Lab of Econometrics and Fujian Key Lab of Statistics,
Xiamen University, Fujian, 361005, China

Abstract: This paper investigates the effect of introducing index futures trading on the spot price volatility in the Chinese stock market. We employ a recently developed panel data policy evaluation approach (Hsiao et al. 2011) to construct counterfactuals of the spot market volatility, based mainly on cross-sectional correlations between the Chinese and international stock markets. This new method does not need to specify a particular regression or a time series model for the volatility process around the introduction date of index futures trading, and thus avoids the potential omitted variable bias caused by uncontrolled market factors in the existing literature. Our results provide empirical evidence that the introduction of index futures trading significantly reduces the volatility of the Chinese stock market, which is robust to different model selection criteria and various prediction approaches.

Keywords: Index futures; Spot market volatility; Panel data; Chinese stock market.

JEL: G14; G1; G15.

[1] We thank Ying Fang, Jin-Chuan Duan, Yongmiao Hong and Doojin Ryu for their valuable comments. Han acknowledges financial support from the Fujian Province National Science Foundation Grant 2011J05009. Standard disclaimer rules apply.
Corresponding author: Qian Han (Assistant Professor), The Wang Yanan Institute for Studies in Economics, Xiamen University, Fujian, 361005, China. Tel: 86-592-2180969. Fax: 86-592-2187708. E-mail: hanqian@gmail.com. Chen (Assistant Professor) can be contacted at hc335@xmu.edu.cn; Li (Assistant Professor) can be contacted at yxli@xmu.edu.cn; Wu (graduate student) can be contacted at wukai@stu.xmu.edu.cn.

1. Introduction

The impact of futures trading on spot market volatility has been a controversial issue in the finance literature for decades. Critics state that futures trading may destabilize spot markets due to excess speculation, especially during turbulent periods such as the U.S. stock market crash of 1987 and the 2007-2009 global financial crisis (see Harris, 1989; Baldauf and Santoni, 1991; Kamara et al., 1992; Darrat and Rahman, 1995; and Pericli and Koutmos, 1997). Another popular argument against futures trading claims that the high degree of leverage in futures markets is likely to attract uninformed traders. The additional "noise" in futures prices could be transmitted to the spot market by arbitrageurs and make prices more volatile. However, supporters of futures markets argue that the introduction of futures trading improves the quality and speed of information flows, expands the feasible risk management tools for investors, and thus makes markets more complete (see Ross, 1977; Breeden and Litzenberger, 1978; Arditti and John, 1980; and McKenzie et al., 2001). Hence, the introduction of futures trading can reduce the volatility of stock markets.

The impact of futures trading on spot market volatility has also been investigated extensively in empirical studies, but the conclusion is no more definitive than that based on the above theoretical arguments (see Antoniou et al., 2005 and Dawson and Staikouras, 2009). Most existing empirical studies, as summarized in Section 2, examine the impact of futures trading using either a two-subsample regression approach or a dummy-variable approach. The former involves estimating two similar regression models in two pre-specified subsamples separated by the introduction date and applying statistical tests, such as the Goldfeld and Quandt (1965) F-test to examine the difference of the residual variances for these two regressions. The latter approach estimates a regression or a GARCH model in the whole sample period, with a dummy variable designed to detect the mean shift in volatility after the introduction of futures trading. Both approaches rely on a time series comparison of estimated unconditional or conditional volatility before and after the event. However, one problem with these methods is the existence of uncontrolled market factors or structural changes that affect market volatility (see Bhattacharya et al.,1986 and Bologna and Cavallo, 2002), which may cause some omitted variable bias on the estimation of the impact of futures trading.

Different from the previous literature, this paper identifies the impact of introducing index futures trading on spot market volatility with a panel data policy evaluation approach developed by Hsiao et al. (2011). The basic idea is to exploit the cross-sectional dependence between Chinese and other international financial markets to construct the counterfactuals of the Chinese spot market's volatility. The cross-sectional correlations are attributed to the presence of some (unobserved) common factors behind the volatilities processes of these markets, which are well recognized in the finance literature.[2] Compared to the existing approaches, our method does not need to specify a particular regression or a time series model for the volatility process around the event, and thus avoids the omitted variable bias caused by uncontrolled market factors. Furthermore, by constructing a path of treatment effects, our method can measure the scale of the impact dynamically, allowing us to detect when the impact of the futures trading occurs.[3]

While most existing studies in the literature focus on developed markets, particularly the U.S. market, this paper analyzes the Chinese stock market. The case of China is worthy of academic interest for several reasons.

First, China is now the world's second largest economy in terms of both GDP and stock market capitalization. In particular, China has built a close relationship with the rest of the world through international trade and investment. Any change in the Chinese economy or stock market now could potentially have significant influence on the world economy and financial markets. As a part of efforts toward financial liberalization, China has allowed qualified domestic institutional investors (QDIIs) to invest abroad and qualified foreign institutional investors (QFIIs) to invest in the domestic financial markets. It is commonly expected that, with a more flexible exchange rate system and fewer capital controls, the Chinese financial market will continue to play a crucial role in the global financial system. An investigation of the impact of futures trading on the Chinese stock market can enrich the current literature and verify the robustness of previous findings across countries.

Second, the Chinese stock market has its own unique features, characterized by the

[2] It has been well documented that global markets show strong co-movements in both returns and volatility processes, which could be driven by some common factors, see Engle and Marcucci (2006) and Anderson and Vahid (2007).
[3] Bologna and Cavallo (2002) investigate whether the "futures effect" is immediate in reducing Italian stock market volatility using a GARCH model approach.

ownership types of listed firms, investor composition and trading mechanisms. Most listed firms in China are state-owned enterprises (SOEs), and only a small proportion of their shares are tradable. As a result, the market is vulnerable to speculation due to the scarcity of security supplies. Retail investors, who are more likely to be noise traders, are still the major force driving stock market movements, although the role of both domestic and foreign institutional investors is growing. In addition, while regulators maintain a T+1 trading mechanism in the spot market, i.e., stock purchased today cannot be traded until the next trading day, which excludes the possibility of intra-day trading, regulators of the newly-introduced futures market allow traders to sell contracts immediately under a T+0 trading mechanism, which facilitates daily speculative trading. Under these circumstances, one may anticipate empirical results that favor critics of futures trading, i.e., the newly introduced futures market destabilizes the spot market.

However, the Chinese stock market has other features, such as a high level of government regulation and a prohibition on short selling.[4] The newly introduced index futures market, as the first official way to allow investors to short the market, helps investors to quickly convert their negative information into market prices and manage their risk in a downward-trending market. From this perspective, one may believe that the spot market will benefit from an improvement in the price discovery process and an expansion of the set of risk management tools, consequently showing a smaller volatility. It is interesting to determine which side is supported by the empirical evidence of this emerging Chinese futures market.

Third, practitioners, both investors and regulators, are interested in the role of the Chinese futures market within the complete domestic financial system. Concerns over its negative impact on the stability of the spot market appeared to be substantiated as the market fluctuated more than 5 percent in the first few trading days after the introduction of futures trading. Our conversations with professional traders suggest that many institutional investors keep a close eye on the development of this market, and that some profited from market inefficiency in the early stages. Hence this study is quite meaningful to practitioners and

[4] The short selling mechanism is a recent introduction to the market but is not very popular among investors due to high transaction costs and a lack of lenders.

regulators as it sheds light on the functionality of this fast-growing market.

We focus on the monthly volatility changes of the CSI 300 index which is commonly used as a representative index to measure the overall performance of the Chinese stock market. The counterfactual prediction of spot market volatility is constructed using a panel data approach, consisting of the monthly volatilities of several major international market indices as well as several domestic macroeconomic indicators. The difference between the observed value and the counterfactual prediction is used to measure the effects of the index futures trading. We find that the counterfactual predictions of the monthly volatilities of the CSI 300 index are higher than the actual ones in most of the months following the introduction date of futures trading. The mean of the treatment effects is -0.0155, which is significant at the 1 percent level. Compared to the mean of the predicted volatilities (without index futures trading), the mean of the actual monthly volatilities (with index futures trading) is approximately 19 percent lower. This finding is very robust against different model selection criteria and various prediction approaches, as demonstrated in Section 5. Furthermore, different from Bologna and Cavallo (2002), we find that the futures effect only appears from the second month after the introduction of index futures trading.

The remainder of this paper is organized as follows. In Section 2 we provide a literature review of previous empirical studies. In Section 3 we describe the panel data evaluation approach. An overview of the Chinese financial markets and a data description are provided in Section 4 while Section 5 presents empirical results and offers some discussion. Section 6 concludes.

2. Literature Review

A large number of empirical studies examine the impact of futures trading on cash market volatilities. The earliest work investigates whether the Government National Mortgage Association (GNMA) futures trading impacts the volatility of its cash market. Figlewski (1981) finds an increased degree of spot price volatility after introducing futures trading, through a regression analysis for cash market volatility with some futures market-related explanatory variables, such as futures price volatility and futures market liquidity measures. Simpson and Ireland (1982) and Corgel and Gay (1984) use statistical methods to detect changes in the volatility of the GNMA cash market around the date when futures trading commenced, but find no evidence to support the significance of future effects. Bhattacharya et al. (1986) conduct a Granger causality analysis and conclude that future market volatility has a causal influence on cash market volatility but that the evidence is not very strong.

A majority of the follow-up studies focus specifically on the stock market, aiming to explore the relationship between stock futures trading and the volatility of the stock market. While Edwards (1988) reports a lower volatility of the S&P 500 index after the introduction of the stock index futures, Harris (1989) argues that the impact of index futures trading is not economically significant. Schwert (1990) documents that the trading volumes in both index futures and spot markets tend to increase when the volatility of the S&P 500 index goes up. Bessembinder and Seguin (1992) show that the unexpected S&P 500 index futures trading was positively related to spot market volatility but was negative for expected trading. While there is a strong focus on the U.S. markets, many studies examine the impact of futures trading in other stock markets. Lee and Ohk (1992) find that, to some extent, the introduction of futures trading reduces Hong Kong stock market volatility. Similar findings are reported by Chang et al. (1999) for the Nikkei stock market. On the contrary, Antoniou and Holmes (1995) find an increasing volatility after the introduction of the FTSE 100 index futures contracts to the London Stock Exchange. Dennis and Sim (1999) conclude that the introduction of individual share futures contracts has very little impact on cash market volatility in the Australian stock market. These conflicting studies highlight the difficulties in obtaining a definitive world-wide conclusion. Besides the difference across research subjects, one possible reason is that these studies use different model specifications, and thus generate different results.

In the past decade, the literature continues to grow with more sophisticated models looking at broader segments of financial markets. McKenzie et al. (2001) examine the effect of individual stocks futures trading on the systematic risk and volatility of the underlying shares, and find a decline in unconditional volatility but also find rather mixed results for conditional volatility. Bologna and Cavallo (2002) find a reduction of stock market volatility after introducing stock index futures in the Italian stock market and especially, that this futures effect occurs immediately. Antoniou et al. (2005) study the market volatilities of six industrialized nations and provide support to the view that futures markets help stabilize the underlying spot markets. Bohl et al. (2011) use a Markov-switching GARCH model to find that the introduction of index futures trading in Poland does not destabilize the spot market. Similar research has been conducted in other financial markets. For example, Staikouras (2006) examines the impact of futures trading on the spot market volatility of U.K. short-term interest rates using a GARCH-X model. Dawson and Staikouras (2009) study the impact of volatility derivatives on the S&P 500 spot market volatility. Wong et al. (2006) examine forward sale (presale) activities on the volatility of spot prices in the Hong Kong real estate market. Most of these studies use GARCH family models, with various specifications to capture the dynamic properties of the underlying volatility processes; however, omitted variable bias due to uncontrolled market factors still exists. Our approach, based on cross-sectional correlation among a panel data, avoids this bias.

3. Methodology

In this section, the panel data evaluation approach of Hsiao et al. (2011) is extended to examine the impact of the introduction of CSI 300 index futures trading on the spot price volatility.

As in Engle and Marcucci (2006) and Anderson and Vahid (2007), we assume a factor model for the volatilities processes of the CSI 300 index and other major market indices:

$$y_{it} = b_i{}'F_t + \alpha_i + \varepsilon_{it} \qquad i = 1,\ldots,N, t = 1,\ldots,T \tag{1}$$

where F_t denotes the $K\times 1$ time-varying observed or unobserved common factors; b_i denotes the $1\times K$ vector of constants varying across i; α_i denotes the fixed individual effects; and ε_{it} denotes the i-th individual random idiosyncratic component with $E(\varepsilon_{it}) = 0$.

Define $Y_t = (y_{1t},\ldots,y_{Nt})'$ as an $N\times 1$ vector of y_{it}. We let y_{1t} denote the volatility of the CSI 300 index and $y_{2t},\ldots,y_{Nt}$ denote the volatilities for other markets. Now suppose there is a policy intervention (the introduction of index futures trading) on the first individual (the CSI 300 index) from time T_1 onwards. Before T_1, we denote the observed y_{1t} without the intervention as

$$y_{1t} = y_{1t}^0, \quad t = 1, \ldots, T_1.$$

After T_1, the observations of y_{1t} under the policy intervention are denoted as

$$y_{1t} = y_{1t}^1 \quad t = T_1 + 1, \ldots, T.$$

There is no such policy intervention for other markets, thus we have

$$y_{it} = y_{it}^0 \quad i = 2, \ldots, N, \quad t = 1, \ldots, T.$$

For convenience of expression, we define a dummy variable as

$$d_{1t} = \begin{cases} 1, & \text{if the intervention occurs at time } t \text{ for } \mathrm{y}_1 \\ 0, & \text{otherwise} \end{cases}$$

and assume that $E(\varepsilon_{is} | d_{1t}) = 0$ for all $i = 2,3,...,N$ and $s \geq t$, i.e., the idiosyncratic components of other stock markets are independent of the policy intervention.

The treatment effect on y_{1t} is measured by the difference between the actual volatility and the predicted volatility under no intervention, given by

$$\Delta_{1t} = y_{1t}^1 - y_{1t}^0, t = T_1 + 1, ..., T.$$

One difficulty in estimating Δ_{1t} is that we are not able to observe y_{1t}^0 after T_1. Most previous research estimates Δ_{1t} by specifying a conditional volatility model for y_{1t}. However, such a model cannot capture the effect from the latent factors in Equation (1), and thus results in omitted variable bias.

To address this problem, we apply the method of Hsiao et al. (2011) and use the information from $\tilde{y}_t^0 = \left(y^0_{2t}, \ldots, y^0_{Nt}\right)'$ to predict y_{1t}^0.

From Equation (1), we can express

$$y_{1t}^0 = \bar{\alpha} + \tilde{\alpha}' \tilde{y}_t^0 + \varepsilon_{1t} - \tilde{\alpha}' \tilde{\varepsilon}_t \tag{2}$$

where $\tilde{\alpha} = (\alpha_2, \ldots, \alpha_N)'$, $\tilde{\varepsilon}_t = (\varepsilon_{2t}, \ldots, \varepsilon_{Nt})'$. Define $\tilde{\varepsilon}_{1t} = \varepsilon_{1t} - \tilde{\alpha}' \tilde{\varepsilon}_t$, and then

$$y_{1t}^0 = \bar{\alpha} + \tilde{\alpha}' \tilde{y}_t^0 + \tilde{\varepsilon}_{1t}. \tag{3}$$

We choose $(\hat{\bar{\alpha}}, \hat{\tilde{\alpha}})$ to minimize

$$\frac{1}{T_1}\sum_{t=1}^{T_1}\left(y_1^0-\bar{\alpha}-\tilde{\alpha}\tilde{y}_t^0\right)'\left(y_{1t}^0-\bar{\alpha}-\tilde{\alpha}'\tilde{y}_t^0\right). \tag{4}$$

The estimator for y_{1t}^0 can be defined as

$$\hat{y}_{1t}^0=\hat{\tilde{\alpha}}+\hat{\tilde{\alpha}}'\tilde{y}_t^0, \tag{5}$$

and Δ_{1t} can be estimated by

$$\hat{\Delta}_{1t}=y_{1t}-\hat{y}_{1t}^0 \quad t=T_1+1,\ldots,T. \tag{6}$$

Following Hsiao et al. (2011), we show that

$$E\left(\hat{\Delta}_{1t}\middle|\tilde{y}_t\right)=\Delta_{1t} \quad t=T_1+1,\ldots,T. \tag{7}$$

Note that there may exist a serial correlation in the estimated treatment effects. Thus, we use the Box-Jenkins method to construct an ARMA model[5] for $\hat{\Delta}_{1t}$ as

$$\tilde{\alpha}(L)\hat{\Delta}_{1t}=\tilde{\mu}+\tilde{\theta}(L)v_t, \tag{8}$$

where $\tilde{\mu}$ measures the long-run treatment effect of the event. A *t*-statistic can be applied to test whether $\tilde{\mu}$ is significantly different from zero. If $\hat{\Delta}_{1t}$ is a stationary process, the long-run effect of the treatment can be estimated by taking the simple average over *t* and we show that

$$\underset{(T-T_1)\to\infty}{\text{plim}}\frac{1}{T-T_1}\sum_{t=T_1+1}^{T}\hat{\Delta}_{1t}=\Delta_1. \tag{9}$$

When conducting the *t*-test, the heteroskedasticity autocorrelation consistent (HAC) estimator (see Newey and West, 1987) can be applied to estimate the variance of the simple average.

4. Market and Data

4.1 An Overview of the CSI 300 Futures Market

The Chinese stock market has experienced tremendous growth and development within the last twenty years since the inception of the Shanghai Stock Exchange and the Shenzhen Stock Exchange. By the end of 2010, the number of listed companies reached almost 2,000 — up

[5] An ARMA model is a standard approach to capture serial correlations of a time series process, with the order of lags selected by some information criteria, such as Akaike information criterion (AIC) or Bayesian information criterion (BIC).

from only 10 companies in the early 1990s — with a total market capitalization of over RMB 26 trillion (US$ 3.98 trillion), or 81.02 percent of Chinese GDP.[6] It was not until April 16, 2010, when the China Financial Futures Exchange formally introduced CSI 300 index futures contracts, that China had a futures market. This advance was widely regarded as a milestone event in the development of Chinese capital markets.[7]

As a new financial instrument, CSI 300 index futures are strictly monitored by regulators. A stringent set of rules is imposed, including a threshold of RMB 500,000 as the minimum deposit for a single trading account and a margin requirement of 12 percent. Eligible retail investors must have prior experience with either commodities futures trading or the mock trading of index futures. Institutional investors, including equity funds, balanced funds and capital preservation funds, are allowed to participate in futures trading, but not with bond funds or money market funds.[8] In addition, index futures are subject to a +/- 10 percent price band based on the previous close, similar to the spot market.[9] All of these rules reflect regulators' cautious attitudes regarding this nascent financial market.

Though there are high barriers to entry and strict regulation, the index futures market still attracts much attention from investors. After its introduction, the CSI 300 index futures quickly became one of the most actively traded financial products in China. Table I reports the trading volume of the CSI 300 index futures and spot market. Over the first three months of trading, the average monthly trading volume was more than 6 million contracts, with a value exceeding RMB 5 trillion (US$ 800 billion), a number larger than the value of stocks traded on the spot markets during the same period. However, the open interest remained very low (around 12,500 contracts, on average), suggesting that trading volume was mainly driven by speculative day trading. The huge trading volume was also related to the large price spread between the futures and spot markets (22.04 points, on average, in the first month), which inspired arbitrage trading between these two markets. As the profitable price spread

[6] Sources: the annual reports of Shanghai Stock Exchange and Shenzhen Stock Exchange.

[7] Note that both "red chip" (the shares of mainland China companies incorporated outside mainland China and listed on the Hong Kong stock exchange) and "H shares" (the shares of companies incorporated in mainland China that are traded on the Hong Kong stock exchange) have corresponding futures, however, restrictions prohibit mainland Chinese citizens from trading futures and stocks on the Hong Kong stock market.

[8] As part of the government's efforts to further open up China's financial markets, the recently unveiled "Rules on Index Futures Trading for Qualified Foreign Institutional Investors (QFIIs)" allow for QFIIs' participation in the domestic stock index futures market.

[9] Any price quotes beyond this interval will be automatically denied. This mechanism is designed as a cooling-off system to stabilize the market in extremely volatile periods.

disappeared, the trading volume decreased.

Note that the futures and cash markets have a similar trend in trading volume. As the market index reached its peak in November 2010, the trading volume in both the futures and spot market peaked, and both decreased as the market went into a bear regime. This pattern is very typical in financial markets since investors prefer trading in an up-trending market but restrict their activity in a down-trending market.

[Insert Table I about here]

Figure 1 shows the movements of the CSI 300 index daily price from January 4, 2002 to June 30, 2011. It should be emphasized that the index fluctuated between 1,000 and 1,500 most of the time between 2002 and 2005; however, since 2005, China's stock markets have seen greater volatility than before. Having recorded dramatic gains in 2006 and 2007, the markets turned bearish in 2008, and recovered from the bottom at the end of 2008. Since then they have fluctuated between 2,000 and 4,000 with a weak overall performance. It is obvious that the volatility process of the spot market possesses various time-varying properties which make finding a suitable model to capture its dynamics a challenge.

Figure 2 displays the movements of both the daily CSI 300 index futures and the cash price between 2010:M4 and 2011:M6. Note that the Chinese stock market tumbled, with the benchmark CSI 300 index dropping by 27.3 percent, from 3,388 on April 16, 2010 to 2,463 on July 2 of the same year. Did the introduction of index futures trading cause this dramatic change in the cash market price, or is this just a coincidence? The present study determines this while insulating the effects from other events such as the global financial crisis.

[Insert Figure 1 and 2 about here]

4.2 Data and Descriptive Statistics

Our data consists of the daily returns of the CSI 300 index, other major international markets indices, and some domestic macroeconomic indicators. The sample period is from January 2002 to June 2011, the latest data available for the CSI 300 index.

We include the Hang Seng Index (HSI), the Hang Seng China Affiliated Corporation Index (HSCCI) and the Hang Seng China Enterprises Index (HSCEI) in our data set because of the close relationship between the Hong Kong and Chinese stock markets (see Wang and Jiang, 2004 and Kutan and Zhou, 2006). The integration of Hong Kong with China means that they share much closer economic ties, especially as an increasing number of Chinese enterprises go public in the Hong Kong stock market.

We also select some major stock indices of the Asia-Pacific region, such as Korea's Composite Stock Price Index (KOSPI 200), Japan's Nikkei 225 Index, Singapore's Strait Times Index and Taiwan's Composite Index. Aware of the tremendous influence in the international financial markets of industrialized countries, we also include the United Kingdom's FTSE 100 Index, the United States' S&P 500 Index, France's CAC 40 Index, Germany's Frankfurt DAX Index, Brazil's Bovespa Index, Canada's S&P/TSX Composite Index and Australia's All Ordinaries Index.

Apart from stock indices from around the world, several domestic macroeconomic variables are also included in constructing the counterfactual predictions. These include CPI, M1 monthly growth rate, M2 monthly growth rate, the monthly growth rate of industrial production, the interest rate spread between three months and three years as well as the interest rate spread between three months and five years. These variables are commonly used in the finance literature.

Stock index returns and trading data are obtained from the Resset Financial Research Database and the Wind Financial Database; macroeconomic data are from the Financial Statistics Database of the Chinese Academy of Social Sciences as well as the China Statistical Yearbook.

The monthly stock index volatility for each index is calculated as the standard deviation of daily index returns multiplied by the square root of the number of trading days in that month. Table II reports the summary statistics of all the index volatilities and domestic macroeconomic variables.

[Insert Table II about here]

5. Empirical Results

5.1 Results

We implement the method described in Section 3 to detect the impact of CSI 300 index futures trading on the volatility of the Chinese stock market.

According to the introduction date of index futures, we divide the whole sample interval into two periods: the pre-futures period of 2002:M1 to 2010:M4 and the post-futures period of 2010:M5 to 2011:M6. Equation (3) is estimated using the data observations during the pre-futures period and the coefficients of the predicting variables are shown in Table III. We then construct the counterfactual predictions for the post-futures period through Equation (5). We designate the pre-futures period as the in-sample period for model estimation and the post-futures period as the out-of-sample period for forecasting. Note that the counterfactual prediction is constructed using the model estimated without considering the effect of futures trading. Thus, the difference between the actual and predicted values includes both ordinary prediction errors and treatment effects of the introduction of futures trading.

[Insert Table III about here]

Figures 3 and 4 depict the actual and predicted values of the monthly volatility of the CSI 300 index for the in-sample period and the out-of-sample period, respectively. From Figure 3 we see that the monthly volatility of the CSI 300 index before the introduction of futures trading can be accurately predicted by the volatility of several major international indices and domestic macroeconomic variables. Figure 4 shows that the predicted monthly volatilities of the CSI 300 index are higher than the actual ones for most of the months after the introduction of futures contracts, indicating a negative treatment effect. However, further statistical evidence is required to confirm the significance of this effect.

[Insert Figure 3 and 4 about here]

Table IV reports the estimation and testing results of treatment effects over the whole post-futures period. The second column reports the actual monthly volatilities calculated from daily returns while the third column reports the predicted volatilities. The treatment effects, reported in the last column, are defined as the difference between them. The bottom of the table displays the mean of the treatment effects, which amounts to -0.0155 with an HAC-adjusted standard error of 0.0019 and a t-statistic of -7.98, significant at the 1 percent level. The effect is also significant in an economics sense as the mean of the actual monthly volatilities (with index futures trading) is approximately 19 percent lower than the mean of the predicted volatilities (without index futures trading). Our results, consistent with some recent findings for other financial markets (see Antoniou et al., 2005; Dawson and Staikouras, 2009; Bohl et al., 2011), show that the introduction of index futures trading plays an important role in stabilizing the spot market.

[Insert Table IV about here]

Note that the estimated treatment effect for the first month is slightly positive and becomes negative in the second month, implying that the futures effect has a short lag. This result differs from Bologna and Cavallo (2002), who find that the futures effect occurs almost immediately after the introduction of index futures trading in the Italian stock market. However, our result is not surprising given the findings of Yang et al. (2012), which show that in its infancy, the Chinese index futures market does not function well in its price discovery performance. As more intuitional investors join the market, the index futures market starts to function as expected and plays a role in stabilizing the spot market.

To check the significance of long-term treatment effects, we estimate the following ARMA model:

$$\hat{\Delta}_{1t} = \underset{(0.0017)}{-0.0158} - \underset{(0.3384)}{0.6892}\hat{\Delta}_{1,t-1} - \underset{(0.2330)}{0.3941}\hat{\Delta}_{1,t-2} + \hat{\eta}_t,$$

where the estimated standard errors are reported in parentheses. The order of lags is determined by AIC. The implied long-run effect from the ARMA model is -0.0076 with a t-statistic of -6.43, significant at the 1 percent level. The result is consistent with the previous HAC robust t-test.

5.2 Robustness Checks

5.2.1 Variable Selection Based on Information Criteria

The results reported above use all of the market indices and macroeconomic variables as predictors. However, as we have more than 20 variables but only 100 monthly observations, it is suboptimal to take all of the variables into the prediction regression. Following Hsiao et al. (2011), we use a two-step procedure to choose the predicting variables.

Step 1: Use AIC or AIC with a correction (AICC) to select the optimal predictors for y_{1t}^0 using j cross-sectional units out of $(N-1)$ cross-sectional units, denoted by $M(j)^*$, for $j=1,\ldots,N-1$.

Step 2: From $M(1)^*, M(2)^*, \ldots, M(N-1)^*$, choose $M(j)^*$ according to AIC or AICC.

The selected optimal predictors according to AIC are HSCCI volatility, Japan's index volatility, Singapore's index volatility, CPI, M2 growth rate, Interest rate spread 3m-3y and Interest rate spread 3m-5y. The selected optimal predictors according to AICC are HSCCI volatility, M2 growth rate, interest rate spread 3m-3y and interest rate spread 3m-5y. Table V reports the testing results for both cases. The results show that the treatment effects of futures trading are still significantly negative, which further confirms the argument that the introduction of stock index futures reduces the volatility of the Chinese stock market.

[Insert Table V about here]

5.2.2 Principal Component Analysis

Instead of choosing a subset of variables, we can use a principal component analysis to extract common factors from the predicting variables, and then construct counterfactual predictions using these factors. We find that the first five largest components can explain almost 90 percent of the variation of the predicting variables, thus, we choose these components to make our predictions. The estimation and testing results are presented in Table VI. We find that the mean value of the treatment effect is -0.018 with an HAC-adjusted *t*-statistic of -2.54, significant at the 5 percent level. Figures 5 and 6 compare the actual and predicted values of the monthly volatility of the CSI 300 index in the two periods. The results are consistent with the findings in Section 4.

[Insert Table VI about here]

[Insert Figures 5 and 6 about here]

5.3 Discussion

Before concluding that the introduction of index futures trading causes a reduction of the spot market volatility, as detected by our method, we would like to discuss the effectiveness and advantage of our method compared to the traditional approach based on GARCH models.

To illustrate effectiveness, we conduct an experiment using only the data from the pre-futures period. We construct counterfactuals for the monthly volatility of the CSI 300 index with 2002:M1 to 2009:M4 as the in-sample estimation period and 2009:M5 to 2010:M4 as the out-of-sample forecasting interval. If the introduction of futures trading is the reason for the spot volatility reduction, there should be no significant treatment effect at 2009:M4. Table VII reports the results of the experiment. The mean is 0.0102 and is not significant at any reasonable level. The long-term effect implied from the AR model is -0.00016， also not significant with a *t*-statistic of -0.012. These results imply that before the introduction of the CSI 300 index futures, there was no significant difference between predicted and actual volatilities. This experiment demonstrates that our model accurately captures the impact of the CSI 300 index futures on the volatility of the spot market.

[Insert Table VII about here]

To emphasize the advantage of our method, we conduct another experiment using a GARCH model with a dummy variable to detect the effect of introducing futures trading. To increase the sample size on both sides of the event, we use daily returns data. The dummy variable equals one if the observations are after April 15, 2010, and zero otherwise. Table VIII reports the results for different sample periods. We find that the conclusions are very sensitive to the selection of sample periods, a characteristic not shared by our method.[10]

[Insert Table VIII about here]

6. Conclusion

In conclusion, this paper uses a recently developed panel data evaluation approach to explore the impact of the introduction of stock index futures on the volatility of the Chinese stock market. The method relies on the cross-correlations among global stock markets and does not need to specify any particular regression model or time series model, thus avoiding

[10] One may argue that the results could be made more robust by adding more market factors to the conditional variance equation. However, determining which factor and what form should be adopted is a challenging issue best left for future research.

the so-called omitted variable bias evident in previous literature. We find that the introduction of index futures trading significantly reduces the volatility of the Chinese stock market, a finding which is robust to different model selection criteria and various prediction approaches. Our findings support the view that the index futures market, at least in China, improves information efficiency and provides investors with better risk-management tools. However, caution must be applied as this finding may result from the uniqueness of the Chinese financial markets, in particular their strict entry requirements, high margin level and other government regulations. Thus, future research on how these factors affect the impacts of futures markets is needed before extending this conclusion to other markets.

Bibliography

Anderson H. M., & Vahid F. (2007). Forecasting the volatility of Australian stock returns. *Journal of Business and Economic Statistics*, 25, 76–90.

Antoniou, A., & Holmes P. (1995). Futures trading, information and spot price volatility: Evidence for the FTSE-100 stock index futures contract using GARCH. *Journal of Banking and Finance*, 19, 117–129.

Antoniou, A., Koutmos, G. & Pericli, A. (2005). Index futures and positive feedback trading: Evidence from major stock exchanges. *Journal of Empirical Finance*, 12, 219–238.

Arditti, F., & John, K. (1980). Spanning the state space with options. *Journal of Financial and Quantitative Analysis*, 15, 1–9.

Baldauf, B., & Santoni, G. J. (1991). Stock price volatility: Some evidence from an ARCH model. *Journal of Futures Markets*, 11, 191–200.

Bessembinder, H., & Seguin, P. J. (1992). Futures-trading activity and stock price volatility. *Journal of Finance*, 47, 2015–2034.

Bhattacharya, A. K., Ramjee, A., & Ramjee, B. (1986). The causal relationship between futures price volatility and the cash price volatility of GNMA securities. *Journal of Futures Markets*, 6, 29–39.

Bohl, M. T., Salm, C. A., & Wilfling, B. (2011). Do individual index futures investors destabilize the underlying spot market? *Journal of Futures Markets,* 31, 81–101.

Bologna, P., & Cavallo, L. (2002). Does the introduction of stock index futures effectively reduce stock market volatility? Is the 'futures effect' immediate? Evidence from the Italian stock exchange using GARCH. *Applied Financial Economics,* 12, 183–192.

Breeden, D., & Litzenberger, R. (1978). Prices of state-contingent claims implicit in option prices. *Journal of Business,* 51, 621–652.

Chang, E.C., Cheng, J. W., & Pinegar, J. M. (1999). Does futures trading increase stock market volatility? The case of the Nikkei stock index futures markets. *Journal of Banking and Finance*, 23, 727–753.

Corgel, J. B., & Gay, G. D. (1984). The impact of GNMA futures trading on cash market volatility. *Real Estate Economics*, 12, 176–190.

Darrat, A. F., & Rahman, S. (1995). Has futures trading activity caused stock price volatility? *Journal of Futures Markets,* 15, 537–557.

Dawson, P., & Staikouras, S. K. (2009). The impact of volatility derivatives on S&P500 volatility. *Journal of Futures Markets,* 29, 1190–1213.

Dennis, S. A., & Sim, A. B. (1999). Share price volatility with the introduction of individual share futures on the Sydney futures exchange. *International Review of Financial Analysis,* 8, 153–163.

Edwards, F. R. (1988). Futures trading and cash market volatility: Stock index and interest rate futures. *Journal of Futures Markets,* 8, 421–439.

Engle, R. F., & Marcucci, J. (2006). A long-run pure variance common features model for the common volatilities of the Dow Jones. *Journal of Econometrics*, 132, 7–42.

Figlewski, S. (1981). Futures trading and volatility in the GNMA market. *Journal of Finance*, 36, 445–456.

Goldfeld, S. M., & Quandt, R. E. (1965). Some tests for homoscedasticity. *Journal of the American Statistical Association,* 60, 539–547.

Harris, L. (1989). S&P 500 cash stock price volatilities. *Journal of Finance*, 44, 1155–1176.

Hsiao, C., Ching, H. S., & Wan, S. K. (2011). A panel data approach for program evaluation-measuring the benefits of political and economic integration of Hong Kong with mainland China. *Journal of Applied Econometrics*, DOI: 10.1002/jae.1230.

Kamara, A., Miller, T. W., & Siegel, A. F. (1992). The effect of futures trading on the stability of Standard and Poor 500 returns. *Journal of Futures Markets*, 12, 645–658.

Kutan, A. M., & Zhou H. (2006). Determinants of returns and volatility of Chinese ADRs at NYSE. *Journal of Multinational Financial Management*, 16, 1–15.

Lee, S.B., & Ohk, K. Y. (1992). Stock index futures listing and structural change in time-varying volatility. *Journal of Futures Markets*, 12, 493–509.

McKenzie, M. D., Brailsford, T. J., & Faff, R. W. (2001). New insights into the impact of the introduction of futures trading on stock price volatility. *Journal of Futures Markets*, 21, 237–255.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55, 703–708.

Pericli, A., & Koutmos, G. (1997). Index futures and options and stock market volatility. *Journal of Futures Markets,* 17, 957–974.

Ross, S. (1977). Options and efficiency. *Quarterly Journal of Economics*, 4, 129–176.

Schwert, G. W. (1990). Stock volatility and the crash of '87. *Review of Financial Studies*, 3, 77–102.

Simpson, W. G., & Ireland, T. C. (1982). The effect of futures trading on the price volatility of GNMA securities. *Journal of Futures Markets,* 2, 357–366.

Staikouras, S. K. (2006). Testing the stablization hypothesis in the UK short-term interest rates: Evidence from a GARCH-X model. *Quarterly Review of Economics and Finance*, 46, 169-189.

Wang, S., & Jiang, L. (2004). Location of trade, ownership restrictions, and market illiquidity: Examining Chinese A- and H-shares. *Journal of Banking and Finance*, 28, 1273–1297.

Wong, S. K., Yiu, C. Y., Tse, M. K. S., & Chau, K. W. (2006). Do the forward sales of real estate stabilize spot prices? *Journal of Real Estate Finance and Economics*, 32, 289–304.

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, 99–121.

Figure 1. CSI 300 index (daily cash price) 2002:M1-2011:M6

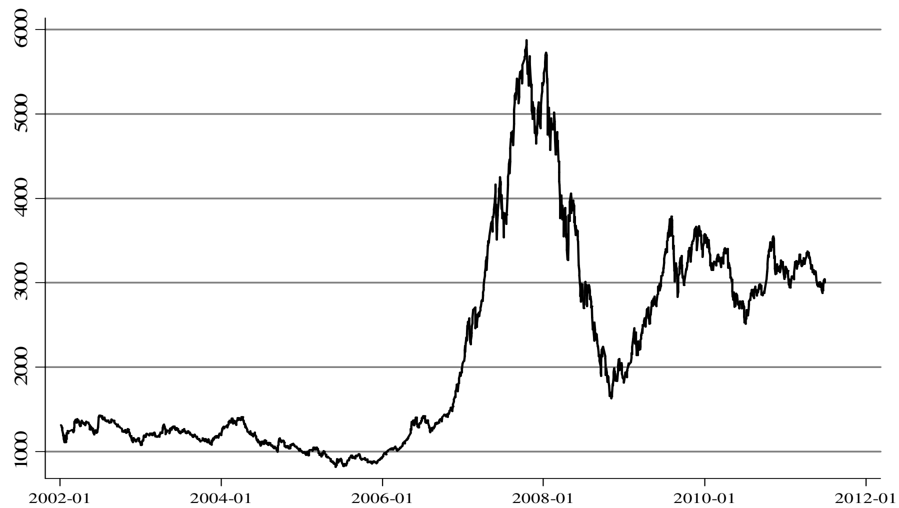

Figure 2. CSI 300 index (daily futures and cash price) 2010:M4-2011:M6

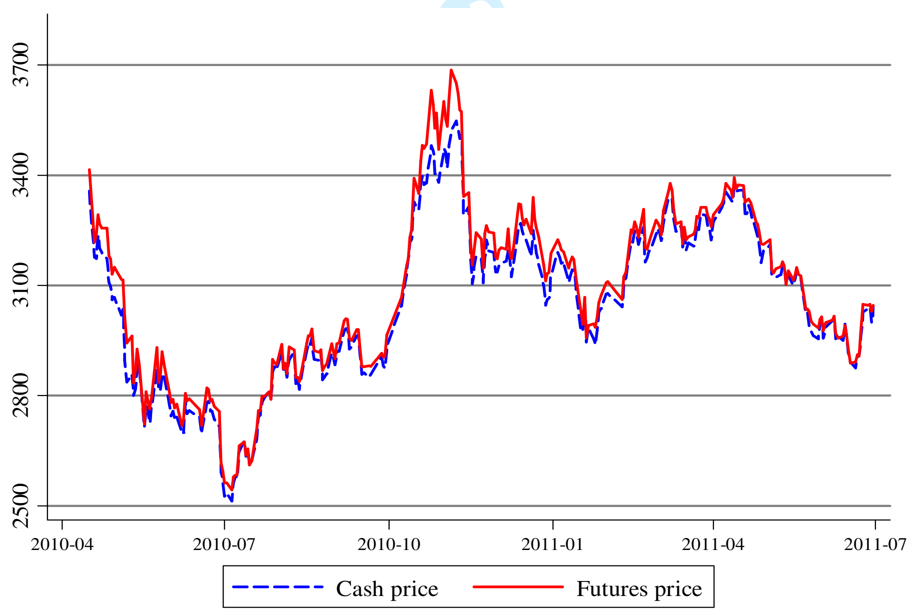

Figure 3. Actual and predicted monthly volatility of the CSI 300 index-panel data evaluation approach 2002:M1-2010:M4

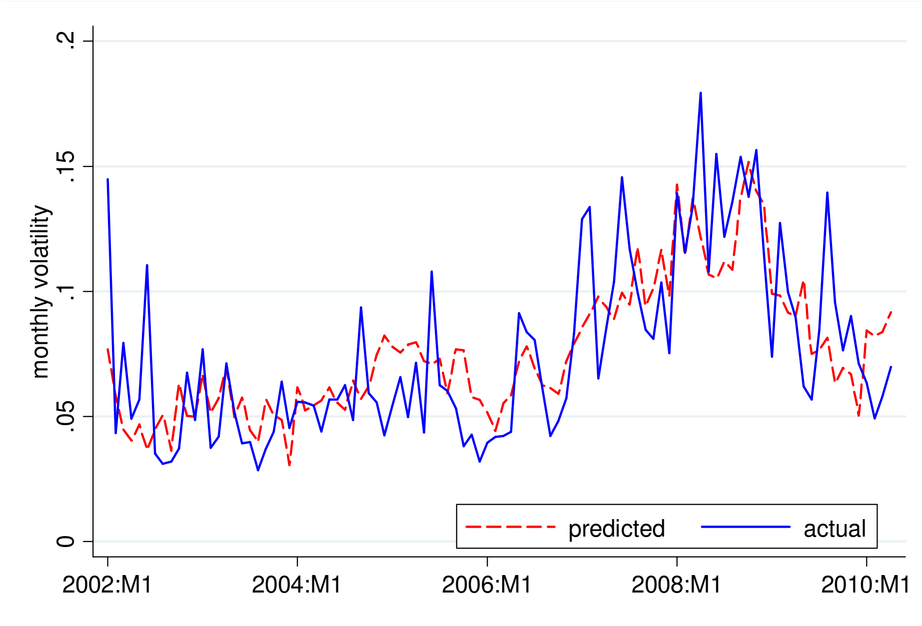

Figure 4. Actual and counterfactual predicted monthly volatility of the CSI 300 index-panel data evaluation approach 2010:M5-2011:M6

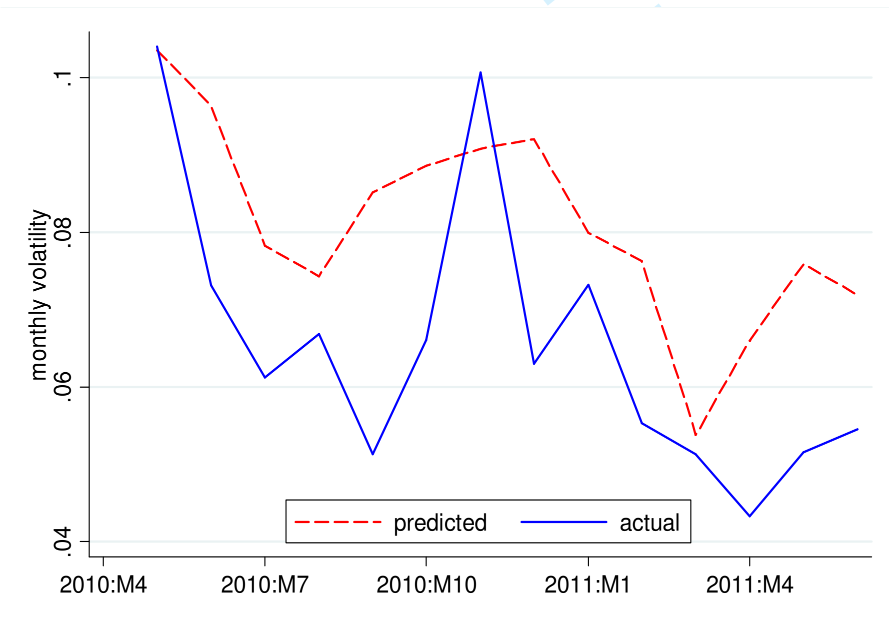

Figure 5. Actual and predicted monthly volatility of the CSI 300 index for principal component analysis 2002:M1-2010:M4

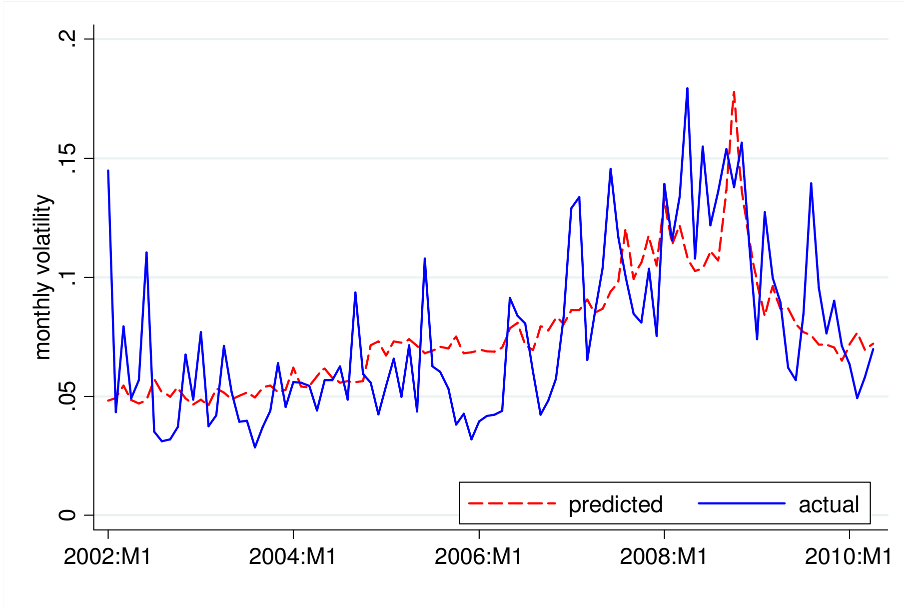

Figure 6. Actual and counterfactual predicted monthly volatility of the CSI 300 index for principal component analysis 2010:M5-2011:M6

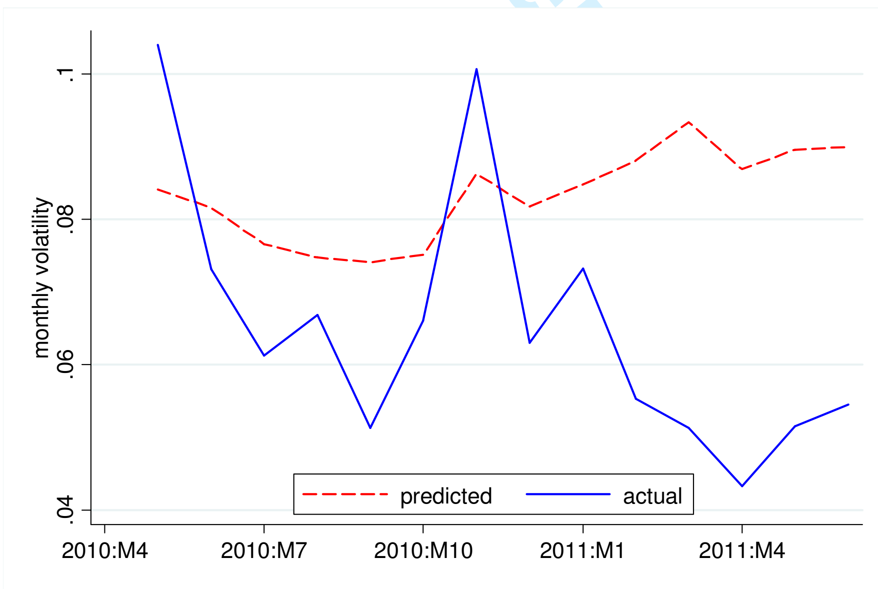

Table I Monthly Trading Volume for Index Futures and Stock Markets

	CSI 300 Index Futures		Stock Markets			
Month	Trading Volume (contract)	Total Turnover (billion RMB)	Trading Volume (million shares)	Total Turnover (billion RMB)	Basis (point)	Open Interest (contract)
2010:M5	5,487,908	4,710	269,119	3,285	22.04	9,630
2010:M6	5,444,545	4,486	212,277	2,531	14.78	12,560
2010:M7	7,536,922	6,055	311,845	3,267	-0.79	15,280
2010:M8	6,965,763	6,052	403,467	4,737	5.99	16,259
2010:M9	4,300,083	3,780	344,783	4,418	11.20	11,704
2010:M10	4,472,644	4,540	467,385	6,284	45.38	22,606
2010:M11	5,646,787	5,672	572,789	8,257	17.25	20,222
2010:M12	4,589,055	4,402	343,275	4,958	17.96	15,665
2011:M1	4,338,211	3,996	258,891	3,470	7.99	11,307
2011:M2	2,987,165	2,862	269,509	3,757	5.51	24,204
2011:M3	4,464,137	4,376	457,194	6,330	7.40	16,810
2011:M4	3,122,689	3,099	361,274	4,593	6.91	20,460
2011:M5	3,413,041	3,169	281,825	3,407	2.43	23,105
2011:M6	3,674,959	3,277	261,225	3,139	1.07	18,453

The trading volume for the CSI 300 Index Futures is calculated as the total number of contracts traded in a particular month. Total turnover represents the total value of all traded contracts in that month. For stock markets, trading volume is calculated as the total number of shares traded in both the Shanghai and Shenzhen Stock Exchanges and the turnover is measured in terms of billions of RMB. The basis is calculated as the monthly average of the daily closing price difference between the CSI 300 index futures in the nearest month and the CSI 300 spot market index. Open interest is the monthly average of the daily open interest of the CSI 300 index futures in the nearest month.

Table II Summary Statistics

	Mean	Std. Dev.	Min.	Median	Max.
Panel A Stock Index Volatility					
CSI 300	0.074	0.034	0.028	0.063	0.179
HIS	0.061	0.039	0.020	0.049	0.321
HSCCI	0.078	0.039	0.027	0.067	0.304
HSCEI	0.082	0.049	0.026	0.067	0.396
Korea	0.064	0.031	0.023	0.055	0.248
Japan	0.064	0.035	0.019	0.055	0.318
Singapore	0.049	0.027	0.018	0.042	0.211
Taiwan	0.058	0.026	0.024	0.051	0.142
U.K.	0.051	0.033	0.018	0.042	0.231
U.S.	0.051	0.035	0.019	0.043	0.244
France	0.063	0.038	0.025	0.051	0.248
Germany	0.064	0.037	0.021	0.051	0.238
Brazil	0.078	0.038	0.037	0.071	0.326
Canada	0.045	0.031	0.013	0.036	0.237
Australia	0.041	0.025	0.012	0.035	0.175
Panel B Macroeconomic Indicators					
CPI	2.330	2.457	-1.199	2.199	8.199
M2 growth rate	0.184	0.037	0.130	0.178	0.297
M1 growth rate	0.176	0.062	0.066	0.172	0.390
IP growth rate	0.149	0.034	0.027	0.157	0.232
Interest 3m-3y	-1.487	0.496	-2.340	-1.620	-0.720
Interest 3m-5y	-1.833	0.574	-2.880	-1.890	-0.090

The stock return data are obtained from the Resset Financial Research Database and the Wind Financial database; macroeconomic data are from the Financial Statistics Database of the Chinese Academy of Social Sciences as well as the China Statistical Yearbook. Stock index volatility is calculated as the monthly standard deviation of the daily return sequence. CPI is 100 times the growth rate compared to the same month of the previous year. M1 growth rate and M2 growth rate denote the monthly growth rate of M1 and M2, respectively. IP growth rate denotes the monthly growth rate of industrial production. Interest 3m-3y and Interest 3m-5y stand for the interest rate spread between three months and three years or three months and five years, respectively.

Table III Weights of Predictive Group by Panel Data Evaluation Approach 2002:M1-2010:M4

	Beta	Se	*t*-statistics
Constant	0.0484	0.0396	1.22
HSI	-0.0102	0.2906	-0.04
HSCCI	0.2140	0.2214	0.97
HSCEI	-0.0360	0.2025	-0.18
Korea	-0.0198	0.1934	-0.10
Japan	-0.2857	0.2093	-1.36
Singapore	0.4926	0.3264	1.51
Taiwan	-0.0439	0.1611	-0.27
U.K.	-0.4250	0.3363	-1.26
U.S.	0.2187	0.3022	0.72
France	-0.1611	0.1191	-1.35
Germany	0.3960	0.2453	1.61
Brazil	0.1183	0.1783	0.66
Canada	-0.2070	0.3539	-0.58
Australia	0.1531	0.2944	0.52
CPI	0.0044	0.0022	2.01
M2 growth rate	-0.1840	0.1952	-0.94
M1 growth rate	0.0321	0.0809	0.40
IP growth rate	0.0443	0.1430	0.31
Interest 3m-3y	-0.2717	0.1800	-1.51
Interest 3m-5y	0.2134	0.1549	1.38

The stock return data are obtained from the Resset Financial Research Database and the Wind Financial database; macroeconomic data are from the Financial Statistics Database of the Chinese Academy of Social Sciences as well as the China Statistical Yearbook. The names of the stock indexes of different countries represent stock index volatilities which are calculated as the monthly standard deviation of the daily return sequence. CPI is 100 times the growth rate compared to the same month of previous year. M1 growth rate and M2 growth rate denote the monthly growth rate of M1 and M2, respectively. IP growth rate denotes the monthly growth rate of industrial production. Interest 3m-3y and Interest 3m-5y stands for the interest rate spread between three months and three years or three months and five years, respectively.

Table IV Treatment Effect by Panel Data Evaluation Approach 2010:M5-2011:M6

Period	Actual	Predicted	Treatment
2010:M5	0.1040	0.1035	0.0005
2010:M6	0.0731	0.0963	-0.0232
2010:M7	0.0612	0.0783	-0.0170
2010:M8	0.0669	0.0743	-0.0074
2010:M9	0.0513	0.0851	-0.0338
2010:M10	0.0661	0.0886	-0.0225
2010:M11	0.1006	0.0908	0.0098
2010:M12	0.0630	0.0920	-0.0290
2011:M1	0.0732	0.0799	-0.0068
2011:M2	0.0553	0.0762	-0.0209
2011:M3	0.0513	0.0538	-0.0025
2011:M4	0.0433	0.0660	-0.0227
2011:M5	0.0516	0.0759	-0.0243
2011:M6	0.0546	0.0719	-0.0173
Mean	0.0654	0.0809	-0.0155
Std. Err.	0.0056	0.0046	0.0019
t-stat.	11.74	17.55	-7.98

Actual values are the monthly volatilities of the CSI 300 index from 2010:M5 to 2011:M6, while the predicted values are the forecast volatilities based on a panel data evaluation approach. The treatment effect is the difference between actual and predicted values. Standard error is the Newey-West (1987) heteroskedasticity-autocorrelation robust standard error and *t*-statistics is the HAC-adjusted version.

Table V Significance of Treatment Effect (AIC and AICC Model Selection)

	AIC		AICC	
	Treatment Effect	AR(2) intercept	Treatment Effect	AR(2) intercept
mean or intercept	-0.0174	-0.0202	-0.0347	-0.0297
Std. Err.	0.0021	0.0026	0.0037	0.0049
t-stat.	-8.29	-7.82	-9.39	-6.13

Treatment effect is the difference between the actual and predicted values. AR(2) intercept is the intercept of the AR(2) model for the estimated treatment effect. Standard error is the Newey-West (1987) heteroskedasticity-autocorrelation robust standard error and *t*-statistics is the HAC-adjusted version. AIC stands for Akaike information criterion and AICC stands for corrected Akaike information criterion.

Table VI Principal Component Analysis-Significance of Treatment Effect

Period	Actual	Predicted	Treatment
2010:M5	0.1040	0.0840	0.0199
2010:M6	0.0731	0.0816	-0.0084
2010:M7	0.0612	0.0766	-0.0153
2010:M8	0.0669	0.0747	-0.0079
2010:M9	0.0513	0.0741	-0.0228
2010:M10	0.0661	0.0751	-0.0091
2010:M11	0.1006	0.0862	0.0144
2010:M12	0.0630	0.0817	-0.0187
2011:M1	0.0732	0.0848	-0.0116
2011:M2	0.0553	0.0881	-0.0327
2011:M3	0.0513	0.0934	-0.0421
2011:M4	0.0433	0.0869	-0.0436
2011:M5	0.0516	0.0895	-0.0380
2011:M6	0.0546	0.0899	-0.0354
Mean	0.0654	0.0833	-0.0180
Std. Err.	0.0056	0.0025	0.0071
t-stat.	11.74	33.40	-2.54

Actual values are the monthly volatilities of the CSI 300 index from 2010:M5 to 2011:M6, while predicted values are the forecast volatilities based on the panel data evaluation approach. The treatment effect is the difference between the actual and the predicted values. Standard error is the Newey-West (1987) heteroskedasticity-autocorrelation robust standard error and *t*-statistic is the HAC-adjusted version.

Table VII Panel Data Evaluation Treatment Effect (2009:M5-2010:M4)

Period	Actual	Predicted	Treatment
2009:M5	0.0621	0.1117	-0.0496
2009:M6	0.0567	0.0639	-0.0072
2009:M7	0.0847	0.0648	0.0200
2009:M8	0.1393	0.0739	0.0654
2009:M9	0.0957	0.0464	0.0493
2009:M10	0.0764	0.0570	0.0194
2009:M11	0.0900	0.0497	0.0404
2009:M12	0.0712	0.0408	0.0304
2010:M1	0.0634	0.0916	-0.0282
2010:M2	0.0493	0.0831	-0.0338
2010:M3	0.0580	0.0917	-0.0338
2010:M4	0.0698	0.1057	-0.0359

Mean	0.0731	0.0734	0.0102
Std. Err.	0.0082	0.0067	0.0135
t-stat.	8.94	10.48	0.76

The in-sample estimation period is from 2002:M1 to 2009:M4 and the out-of-sample forecast period is from 2009:M5 to 2010:M4. Actual values are the monthly volatilities of the CSI 300 index from 2009:M5 to 2010:M4; the predicted values are forecast volatilities based on the panel data evaluation approach and the treatment effect is the difference between actual and predicted values. Standard error is the Newey-West (1987) heteroskedasticity-autocorrelation robust standard error and *t*-statistic is the HAC-adjusted version.

Table VIII Comparison of Model Robustness with Different Sample Periods

Panel A GARCH (1,1) Model

	β_0	β_1	α_0	α_1	α_2	γ	Obv. #
2002:M1-2011:M6	0.0002	0.0283	-12.6525***	0.0723***	0.9192***	0.2011	2295
	(0.0003)	(0.022)	(0.253)	(0.007)	(0.008)	(0.312)	
2005:M1-2011:M6	0.0008**	0.0278	-12.788***	0.0542***	0.9400***	-0.2279	1525
	(0.0003)	(0.026)	(0.357)	(0.007)	(0.008)	(0.399)	
2006:M1-2011:M6	0.0009*	0.0311	-12.0506***	0.0623***	0.9268***	-0.4463	1333
	(0.0005)	(0.028)	(0.311)	(0.009)	(0.010)	(0.298)	
2007:M1-2011:M6	0.0004	0.0232	-11.6252***	0.0468***	0.9374***	-0.8528***	1092
	(0.0006)	(0.031)	(0.374)	(0.009)	(0.013)	(0.260)	

Panel B Panel Data Evaluation Approach

Treatment	2002:M1-2011:M6	2005:M1-2011:M6	2006:M1-2011:M6	2007:M1-2011:M6
Mean	-0.0155	-0.0189	-0.0153	-0.0356
Std. Err.	0.0019	0.0039	0.0062	0.0127
t-stat.	-7.98	-4.84	-2.47	-2.80
Obv. #	100	64	52	40

Note: In Panel A, the GARCH (1,1) model with a dummy variable is formulated as $R_t = \beta_0 + \beta_1 R_{t-1} + \varepsilon_t, \varepsilon_t \left| \phi_{t-1} \sim N(0, h_t) \right.$, $h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1}^2 + \gamma D_F$ by the maximum likelihood technique. The dummy variable, D_F, takes a value of one if the observations are after April 15, 2010, and is zero otherwise. In Panel B, the treatment refers to the difference between actual and predicted monthly volatility where the actual values are monthly volatilities of the CSI 300 index from 2009:M5 to 2010:M4 and the predicted ones are forecast volatilities based on the panel data evaluation approach. Standard errors are presented in parentheses and *, **, *** denote significance levels of 10%, 5% and 1%, respectively.