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Index volatility and the put-call ratio: a tale of three markets

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This paper investigates the influence of the put-call-ratio (PCR) implied by the Shanghai Stock Exchange (SSE) 50 ETF option on the price discovery process of the SSE50 index, on both the spot and the futures markets. By constructing an asymmetric VARX-MGARCH model, this paper examines the relationship between the PCRs and SSE50 index (futures). Empirical results indicate an asymmetric V-shaped relationship between the PCRs and the conditional volatility of the stock index returns and the index futures returns. The conditional volatility increases as the PCRs deviate widely from the mean. This study suggests that the PCRs implemented in many trading practices may be misused, because there is no evidence that the PCRs and index returns are correlated. Instead, this research implies a different way of using them: to trade volatility.

Keywords: SSE50-ETF; Futures; Option; PCR; MGARCH

JEL Classification: E32, G11, G14, G15

1. Introduction

Past literature documents that the option market reveals the trading behavior of informed investors through their derivatives positions (Ge *et al.* 2016). Therefore, this paper exploits more information from option trading, as doing so is important for and consistent with the recent boom of studies on these topics. For example, researchers are keen to create various measurements such as price-based implied volatility (Xing *et al*. 2010, Cremers and Weinbaum 2010) or corporate events (Jin *et al.* 2012, Chan *et al.* 2015, Hayunga and Lung 2014) in order to predict the future evolution of the stock market.

In this paper, we focus on the daily put-call ratio (PCR) to examine the option market. The PCR is a convenient gauge of trading behavior. It is a ratio constructed by the number of open interest in put options against that in call options in a given time period. Relative to other indicators, the PCR is highly intuitive and straightforward. Furthermore, it is forward-looking, easy to understand, and widely believed to be informative in practice.

A pioneering study by Easley *et al*. (1998) indicates that the option volume by itself can be informative for stock price movements and also shows that option trading is information-based in nature. The follow-on research suggests that a trading volume-based PCR is a good forward-looking indicator. Research by Blau *et al*. (2014) compares the two commonly used ratios for forecasting stock returns: PCR and OSR (Option-to-Stock Volume Ratio). The study shows that the PCR contains more information at a daily level, while the OSR performs well only at the weekly or monthly level. Similarly, Bandopadhyaya and Jones (2011) and Weir (2006) find better explanatory power in the PCR than the Volatility Index (VIX). Moreover, a study by Billingsley and Chance (2009) examines the predictive power of the PCRs for both the Chicago Board Options Exchange (CBOE) equity options and the S&P 100 Index Option (OEX), and argues PCRs can be used to predict the direction of the market. Recent works tend to support this argument, for example, Connors (2012), Houlihan and Creamer (2014), Mehta and Patel (2014), Blau and Brough (2015) and Wu *et al*. (2016). However, mixed evidence is also documented by Pan and Poteshman (2006), which investigates the information content of the PCRs for option contracts that are traded out of the money. Chang *et al.* (2009) also use this model to examine the Taiwan Capitalization Weighted Stock Index (TAIEX) options. Results strongly

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indicate that the PCR constructed from the trading volume carries no valid information on the spot index return.

However, in contrast to the large amount of documented results in developed markets, research on the Chinese index/ETF option market is both inadequate and inconclusive. There are mainly trading-oriented institutional reports on the PCR in a descriptive form. This paper is keen to fill this blank and thereby exhibits a wider view of the Chinese financial derivatives markets.

The SSE50-ETF option contract which tracks the Shanghai Stock Exchange (SSE) 50 index was introduced and listed on the Shanghai Stock Exchange in early 2015. Until recently, the SSE50-ETF option market has attracted enormous attention due to its fast expansion and the SSE50-ETF option market was rapidly ranked the fifth most-traded ETF option worldwide.† Hence, one must examine closely how to extract and interpret information from this market. On this matter, various PCR measurements are constructed and tested in trading practice.‡ Founder Securities Research (2015) looks into the China SSE50-ETF market using a simple autoregressive model and finds that the residuals of the model can be attributed to non-economic factors such as sentiment, of which the PCR (of the SSE50-ETF option) is among the most suitable. In particular, large falls of the PCRs tend to signal market bottoms. But most of these statements are descriptive without a solid robustness proof. China SSE50-ETF Investment Guidelines (2004)§ summarizes the role of the PCR as providing investors with a way to reduce market risk in a bearish situation. This paper is therefore motivated to fill this gap and study the potential effect of the PCR on index return and volatility.

Apart from a direct relationship between the PCR and the spot index (cash market) as examined by previous studies, this price discovery mechanism is also likely to connect to the index futures market. Literature suggests that the futures market generally leads the cash market and serves as the primary market for price discovery. For example, a series of pioneer studies such as Kawaller *et al*. (1987), Cheung and Ng (1990), and Chan *et al*. (1991) all present evidence suggesting that the S&P 500 futures lead the underlying cash index. Furthermore, follow-on research on this topic shows that this effect is both significant and conditional. For example, Chatrath *et al.* (2002) show clear evidence that this information advantage is only valid when the market is booming. There are also studies investigating the relationship between stock volatility and the basis (Chen *et al*. 1995, Chatrath *et al*. 2002, Kogan *et al*. 2009, Yang *et al*. 2012). The results show this correlation is negative, time-varying and conditional. In addition, research focusing on the Chinese market has emerged in recent years after the China Financial Futures Exchange (CFFEX) started trading index futures with the underlying indices of CSI300 in 2010, and CSI500 and SSE50 in 2015.¶ A study by Yang *et al*. (2012) finds that the cash market plays the more dominant role in the price discovery process and hence indicates that the index futures market is still underdeveloped in China.

However, there is little research combining the cash market, the index futures market and the PCR series from the option market so as to investigate the price discovery or volatility dynamics across all three markets. This study contributes to the existing literature by incorporating the PCR into the whole price discovery process and evaluating its predictive power. It is after all possible that this relationship exhibits some complexity when the underlying product (the Chinese A-share stock market) is highly volatile. Therefore, we are also motivated to test the influence of higher moments and justify the robustness of our findings. Furthermore, the identification of the index option behavior in special periods such as a market crash shows some insights for policymakers and market participants. Specifically, this study tests both realized and conditional volatility.

To sum up, the contribution of this paper is threefold: First, we show there is no evidence that the PCR can predict movement in any direction of the SSE50 index. This is different from international experience. This may be attributed to the fact that index futures are more widely used for risk hedging but not the options, and that delta-hedging behaviors among option sellers would blur the relationship in practice. Therefore, our empirical results imply a potential misuse of the PCR as a predictor of index returns in trading practice. Second, we find a significant asymmetric V-shaped relationship between the PCR and conditional variance of index returns, which is valid both for the stock index and its futures. Specifically, conditional variance increases either when the PCR goes up or down from its long-term mean. Third, this study is the very first to examine the relationship between the PCR and the SSE50 index (and its futures), not only in the conditional mean but also in conditional variance. Our research indicates the possible misuse of the popular PCR-related strategies and a potentially correct way of using it: to trade on volatility.

The rest of the paper is structured as follows: Section 2 describes the methodology; Section 3 outlines the dataset and variables; Section 4 presents the empirical results; Section 5 concludes the paper.

2. Methodology

2.1. Linear model

Our study follows Pan and Poteshman (2006) to construct a simple linear model as our benchmark to link the PCR and future stock index returns:

$$R_{t+\tau} = \alpha + \beta PCR_t + \gamma X_t + \varepsilon_{t+\tau}, \tau = 1, 2, \ldots, T \qquad (1)$$

where $R_{t+\tau}$ denotes the daily logarithmic return of the SSE50 index on the day $(t+\tau)$; X_t denotes the control variables; and $\mathrm{PCR_t}$ denotes the put-call ratio implied by the outstanding SSE50-ETF options on day t. The null hypothesis is that the

† Statistics are shown in Table 1.
‡ Gang *et al.* (2019) also investigate the predictability of the 50ETF option.
§ Huaxia Fund Management Co., Ltd., which is the only manager of the SSE50-ETF, is obligated to compile and update these guidelines.
¶ The CSI300 and CSI500 indices are capitalization-weighted stock market indices designed to replicate the performance of major stocks traded on the Shanghai and Shenzhen stock exchanges. Tickers for CSI 300, CSI 500, and SSE50 index futures are IF, IC, and IH, respectively.

Table 1. Trading volumes of top5 ETF index options.

Rank	ETF index option	Jan–Dec 2016	Jan–Dec 2015	% change
1	SPDR S&P 500 ETF Options	671,661,453	655,942,274	2.40%
2	iShares Russell 2000 ETF Options	140,662,647	138,135,687	1.80%
3	Powershares QQQ ETF Options	111,873,109	120,174,871	– 6.90%
4	iShares MSCI Emerging Markets ETF Options	87,941,483	78,473,551	12.10%
5	SSE50-ETF Option, Shanghai Stock Exchange	79,069,347	23,269,976	239.79%

Notes: Data of SSE50 options is from WIND database, other data is from FIA 2016 Volume Survey.

stock market and options market are in separate equilibrium and that the information variable (PCR) has no predictive power at all, that is to say, for all $\tau = 1,2,\ldots,T$, $\beta = 0$.

Apart from the stock index return, we also evaluate the predictive power of the PCR on stock index volatility (realized volatility):

$$Vol_{t+1,t+\tau} = \alpha + \beta PCR_t + \gamma X_t + \varepsilon_{t+\tau}, \tau = 1,2,\ldots,T$$

where $Vol_{t+1,t+\tau}$ denotes the standard deviation of logarithmic return of the SSE50 index between date $t+1$ and $t+\tau$.

2.2. *The asymmetric VARX-MGARCH model*

In order to investigate the influence of the basis (Yang *et al.* 2012) and PCR in the conditional mean and volatility in both cash (spot index) and index futures markets, we revise the model introduced by Yang *et al.* (2012) and construct the following asymmetric VARX-MGARCH model with diagonal-BEKK specification in the conditional variance function. Our conditional mean function is:

$$\begin{aligned}\Delta X_t &= \mu + \Gamma \Delta X_{t-1} + \gamma \max(E_{t-1},0)\\ &\quad + \eta \min(E_{t-1},0) + \delta \max(PCR_{t-1} - \mu_{PCR},0)\\ &\quad + \theta \min(PCR_{t-1} - \mu_{PCR},0) + \varepsilon_t \end{aligned} \tag{2}$$

where $X_t = (X_{1t}, X_{2t})'$; ΔX_{1t} and ΔX_{2t} represent the underlying SSE50 index (log) return and the IH futures (log) return, respectively; E_t is the basis calculated as the difference between the logarithmic stock index and its logarithmic futures price; μ_{PCR} is a long-term mean of the PCR; and γ, η, δ, and θ are coefficients capturing the asymmetric effects of the basis and PCR, respectively.

A multivariate GARCH (MGARCH) model is used for the conditional variance (Baba *et al.* 1990, Engle and Kroner 1995). However, the number of parameters to estimate in the MGARCH is typically large and rises exponentially with the number of variables. In fact, there are $k(k+1)/2$ parameters of variance and covariance for k returns. In addition, the positive-definite constraints need to be satisfied as the covariance matrices are positive definite.

To solve these problems, many parametric formulations are introduced for the structure of the conditional variance-covariance matrices. Baba *et al.* (1990) introduce the BEKK (Baba-Engle-Kraft-Kroner) model that has been widely used. The conditional variance-covariance matrix of the full (unrestricted) BEKK model is:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{3}$$

In Equation (3), C, A, and B are k by k matrices, in which C is upper-triangular. An advantage of the BEKK model is that H_t is positive definite if the diagonal elements of C are positive. But the model contains too many parameters that do not represent directly the impact of ϵ_{t-1} or H_{t-1} on the elements of H_t. In other words, it is hard to interpret the parameters of a BEKK model. Literature also documents evidence that many parameter estimates of the BEKK model are statistically insignificant, implying the model is over-parameterized (Tsay 2006). In fact, a further simplified version of the BEKK model in which A and B are diagonal is more frequently used in practice. The diagonal-BEKK model can be estimated without difficulty and ensures positive definiteness (Silvennoinen and Teräsvirta 2009).

Therefore, an augmented diagonal-BEKK model is then implemented where both matrices A and B are assumed diagonal. By doing so, the number of parameters can be significantly reduced while maintaining the advantage of positive-definite in the conditional variance-covariance matrix.

To further test any potential influence of the PCR on the variance, we then extend the conditional variance model to allow potential PCR effects. The model can be written as follows:

$$\begin{aligned}H_t &= C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B\\ &\quad + F\Sigma_{basis,t-1}F' + G\Sigma_{PCR,t-1}G'\end{aligned} \tag{4}$$

where

$$\Sigma_{basis,t-1} = \begin{bmatrix}\max(E_{t-1},0) & 0\\ 0 & -\min(E_{t-1},0)\end{bmatrix}$$

$$\Sigma_{PCR,t-1} = \begin{bmatrix}max(PCR_{t-1} - \mu_{PCR},0) & 0\\ 0 & -min(PCR_{t-1} - \mu_{PCR},0)\end{bmatrix}$$

The specification as represented in Equation (4) can reveal potential nonlinearities caused by the basis and PCR. Specifically, the sign/significance of the elements in the coefficient matrices F and G would suggest any possible asymmetric effect caused by the basis and PCR, respectively.

To sum up, our full model is built up by Equation (5) and (6) as follows:

$$\begin{aligned}\Delta X_t &= \mu + \Gamma \Delta X_{t-1} + \gamma \max(E_{t-1},0) + \delta \min(E_{t-1},0)\\ &\quad + \eta \max(PCR_{t-1} - \mu_{PCR},0)\\ &\quad + \theta \min(PCR_{t-1} - \mu_{PCR},0) + \varepsilon_t\end{aligned} \tag{5}$$

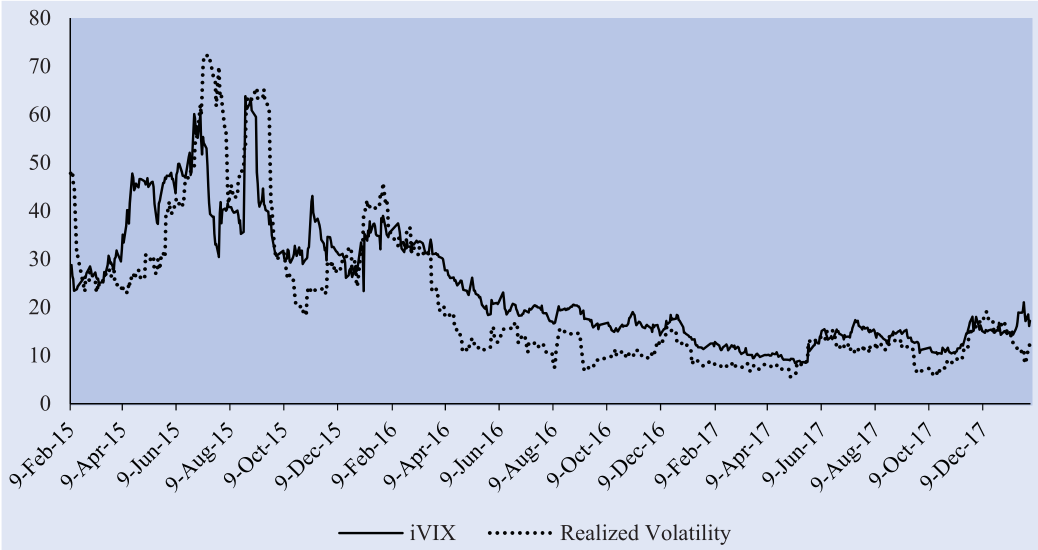

Figure 1. iVIX and realized volatility.

where

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix},\ \Gamma_i = \begin{pmatrix} \Gamma_{11} & \Gamma_{12} \\ \Gamma_{21} & \Gamma_{22} \end{pmatrix},\ \gamma = \begin{pmatrix} \gamma_1 \\ \gamma_2 \end{pmatrix},$$

$$\delta = \begin{pmatrix} \delta_1 \\ \delta_2 \end{pmatrix},\ \eta = \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix},\ \theta = \begin{pmatrix} \theta_1 \\ \theta_2 \end{pmatrix},\ \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$$

and,

$$\begin{aligned} &\varepsilon_t|\Omega_{t-1} \sim D(0, H_t) \\ &H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \\ &\quad + F\Sigma_{basis,t-1}F' + G\Sigma_{PCR,t-1}G' \end{aligned} \tag{6}$$

where

$$C = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix},\ A = \begin{pmatrix} a_{11} & 0 \\ 0 & a_{22} \end{pmatrix},\ B = \begin{pmatrix} b_{11} & 0 \\ 0 & b_{22} \end{pmatrix},$$

$$F = \begin{pmatrix} f_{11} & f_{12} \\ f_{21} & f_{22} \end{pmatrix},\ G = \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix}$$

The above diagonal-BEKK model is estimated by the full-information maximum likelihood method. The log likelihood can be expressed as follows:

$$L = -\frac{1}{2}\sum_{t=1}^{T}(n\log(2\pi) + \log|H_t| + \varepsilon'_t H_t^{-1}\varepsilon_t)$$

All parameters are estimated by maximizing the log-likelihood function as shown by the above function L. To ensure easy identification of parameters as well as meaningful estimates, the calculation burden of a complex L can be easily alleviated by a diagonal-BEKK specification.

Since the conditional variance is specified as a diagonal-BEKK form, there is no straightforward parameter that can be interpreted as the volatility co-movements between the two markets. Therefore, we compute the time-varying cross-market conditional correlation: $CC_t = \frac{h_{12t}}{(h_{11t}h_{22t})^{1/2}}$ to measure the volatility linkage across the two markets, where h_{11t} and h_{22t} are conditional variances of the spot market and futures market, and h_{12t} is conditional covariance of the two.

3. Dataset and variables

The full data panel of the SSE50 index, SSE50 index futures (IH50), and the SSE50-ETF option contracts are drawn from the Wind database.† Our dataset consists of daily trading information of all SSE50 ETF option contracts, including types of options (call/put), option characteristics (strike price and time to maturity), prices, trading volumes, and open interests. The time period is from 16th April 2015‡ to 28th September 2018, covering 890 trading days and 1,488 option contracts in total. In order to construct a continuous nearest futures price series, we follow Yang *et al.* (2012) to use the prices of the nearest futures contract until the contract reaches the first day of the delivery month. Then, prices for the next nearest contract are used. The nearest futures contract is used because it is almost surely the most active and liquid contract given a certain time point (trading day). Thereby, we build a return series by taking the first difference of the logarithms of the futures prices. The time series of the basis in this study is calculated as the difference between the logarithmic stock index and its logarithmic futures price.

In this research, a measurement of the 20-trading-day realized volatility is used to proxy the implied volatility, because the iVIX, which was the Chinese counterpart of the CBOE VIX and officially released by China Securities Index Co., Ltd, was suspended in early 2018. The patterns of both time series are shown in Figure 1. Figure 1 shows a similarity between the iVIX and the realized volatility that we use. It is clear that the implied volatility of the SSE50-ETF option has a pattern of faster-hiking and slower-cooling than the realized volatility, which suggests greater difficulties to build-up short positions using SSE50-ETF options. Figure 1 also shows a period of volatility moderation across 2016 and 2017, which

† The Wind financial database (http://www.wind.com.cn/) is the largest vendor of professional financial data and information on Chinese stocks, bonds, funds, futures, RMB rates, and the macroeconomy.
‡ The start date is the day on which the SSE50-ETF option was officially introduced to the market.

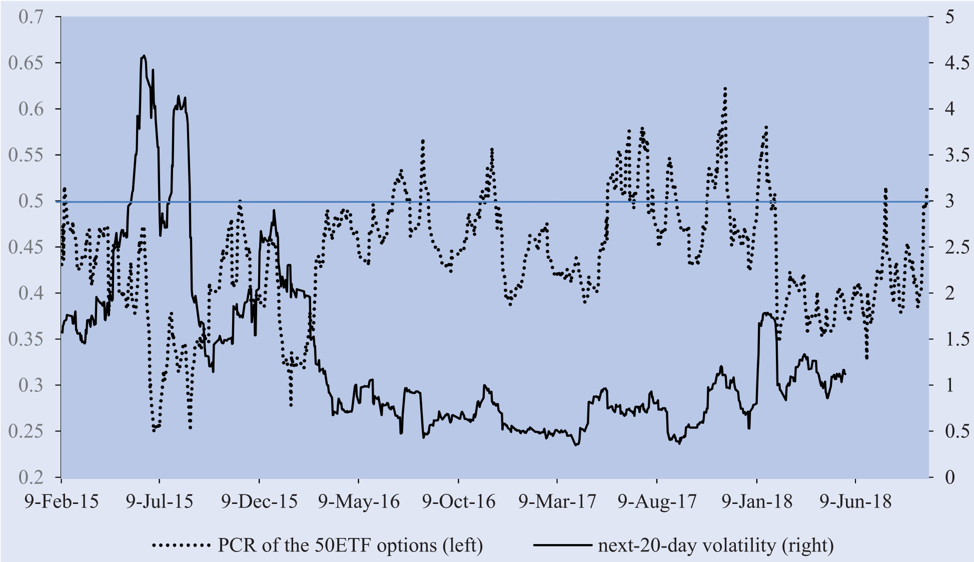

Figure 2. PCR of SSE50-ETF options and realized volatility of SSE50 index.

Table 2. Symbol and explanations of variables.

Variables	Symbol	Explanations
Put-call Ratio	PCR	Open interests of the put options divided by the sum of the open interests of put and call options
Control variables	X_t	Variables that may contain explanatory power on dependent variables other than independent variables
Return	$R_{t+\tau}$	Return of SSE50 on the $t + \tau$ trading day
Volatility	$\mathrm{Vol}_{t+1,t+\tau}$	Standard deviation of SSE50 index return between $t + 1$ and $t + \tau$ day which is a proxy for index volatility
Control 1	Dummy $\times$ near maturity PCR	Interaction term between a dummy variable and the near-mature PCR: dummy variable $= 1$ when there are options mature on next trading day near-mature PCR $=$ PCR calculated by options matured on next trading day
Control 2	Volume	Daily closing SSE50 index trading volume
Control 3	$\mathrm{R}_{-5,-1}$	Past five-day SSE50 index cumulative return

Notes: Other mentioned but not adopted variables are given explanations in the context.

is accompanied by a bullish stock market. In practice, put options are often shorted during a bullish market and this is consistent with high PCRs during that time (as shown by Figure 2). Therefore, the PCR on each day reflects views towards the future of the stock market.

In this study, among several approaches to calculate the PCR, we implement the open interest approach of Fodor *et al*. (2011) as follows:

$$PCR_t = \frac{P_t}{P_t + C_t}$$

where Pt and Ct are the numbers of the open interests of put and call options at time t, respectively. The above calculation ensures all PCR values are positive and less than 1. As argued by Fodor *et al*. (2011), this approach is less volatile than the volume approach but very informative, and is less affected by very short, intraday speculations.

All variables in this research are listed in Table 2. Descriptive statistics of key variables are listed in Table 3.

Table 3 suggests that the number of the call-option open interests is more than that of the put option in general (by noticing the mean of the PCR is below 0.5), and this is consistent with existing studies on developing countries (Chan *et al*. 2009).† This finding is also reinforced by Figure 2 by seeing that most of the values of the PCR (left vertical axis)

Table 3. Descriptive statistics.

	Mean	Standard Deviation	Lowest	Highest
Cash return	– 0.02	1.58	– 9.85	7.55
Futures return	– 0.03	1.78	– 10.37	10.60
Basis	– 0.74	1.29	– 15.13	3.11
PCR	0.44	0.07	0.25	0.63

Notes: Basic descriptive statistics of independent and dependent variables are listed.

† This is, however, different from the evidence from developed markets (Bollen and Whaley 2004).

Table 4. Predictability of PCR on SSE50 index return with varying moneyness.

(Sub-) samples	Constant	PCR	D–W test	White test	R2
Full-Sample	– 0.0053 (– 0.95)	0.0120 (1.02)	1.92	89.5***	0.0024
Above 10% OTM	– 0.0017 (– 1.21)	0.0025 (1.56)	1.91*	39.0***	0.0036
3–10% OTM	– 0.0024 (– 1.36)	0.0049 (1.63)	1.91*	23.3***	0.0027
Near-the-money	– 0.0061 (– 1.43)	0.0146 (1.44)	1.93	0.04	0.0037
3–10% ITM	0.0005 (0.46)	– 0.0013 (– 0.46)	1.90*	10.8***	0.0003
Above 10% ITM	0.0006 (0.85)	– 0.0020 (– 1.03)	1.90*	20.94***	0.0019

Notes: This table reports the results of regressing the next-day SSE50 index daily return on both the whole-sample of current-day PCR and the five categories of the current-day PCR. Five categories are divided according to the option moneyness. OTM denotes out-of-the-money options, and ITM denotes in-the-money options. Near-the-money refers to the call and put options having a strike to price ratio between 0.97 and 1.03. *T*-statistics reported in parentheses are computed from Newey-West standard errors as there are severely heteroscedasticity problems. One, two and three asterisks (*) respectively indicate the *t*-values are significant at the 0.1, 0.05 and 0.01 level.

are below 0.5. Figure 2 also exhibits some negative correlation between the SSE50 index return realized volatility and the PCR. This relationship is likely to be time-varying.

4. Empirical results

4.1. PCR predictability on the SSE50 index return

We follow the approach used by Pan and Poteshman (2006) to regress the next-day return of the SSE50 index on a constant and the daily PCR (shown by Model (1)), and, in the meantime, control for the 'moneyness' (in/out of the money or at the money) of the options. Results are shown in Table 4, in which the leverages of the options are of decreasing order from top to bottom (from extremely out of the money to extremely in the money). In Table 4, coefficients of the PCR, regardless of the moneyness, are all statistically insignificant based on heteroscedasticity and autocorrelation consistent (HAC) *t*-tests by Newey and West (1987). Together with very low R^2s in all the regressions and heteroscedasticity (White tests) in residuals, Table 4 implies the model used by Pan and Poteshman (2006) does not work in China, and that the PCR does not provide any information to forecast the next-day returns. These results, however, are consistent with the findings in TAIEX options by Chang *et al*. (2009).†

4.2. Univariate models of the realized volatility

In general, because the option market is the major place to trade volatility, it is reasonable that the PCR may contain information about stock market volatility. Past literature also indicates the PCR is a reflection of market sentiment (Simon and Wiggins 2001, Dennis and Mayhew 2002) and market sentiment fluctuations can cause prices to be more volatile (Dumas *et al*. 2009). Therefore, it is possible that the PCR would not directly affect the index return, but its volatility instead. This section extends our investigation to examine the predictability of the PCR on the realized volatility of the SSE50 index returns. Regressions such as those in Model (1)

Table 5. Descriptive statistics of SSE50 index volatility.

	Mean	Standard deviation	Lowest	Highest
5-day volatility	1.28	1.04	0.11	7.30
20-day volatility	1.36	0.89	0.35	4.58
60-day volatility	1.37	0.82	0.45	3.80

Notes: Basic descriptive statistics of SSE50 index volatility are listed.

are repeated but with a different dependent variable (realized volatility). Three different rolling windows, 5, 20, and 60 days, are implemented to compute the realized volatility. Descriptive statistics of 5-day, 20-day and 60-day realized volatility are listed in Table 5.

In addition, we separate the PCR into PCR_{upper} and PCR_{lower} relative to the long-term mean of the PCR (denoted by μ_{PCR}): $PCR_{upper} = \max(PCR\text{-}\mu_{PCR}, 0)$; $PCR_{lower} = \min(PCR\text{-}\mu_{PCR}, 0)$. By doing so, we can reveal the asymmetric effects of the PCR on future volatility. Results are reported in Table 6.

Table 6 shows that only the lower PCRs explain the future realized volatility and they perform better for shorter time horizons (5-day and 20-day windows). All coefficients corresponding to the upper PCRs are not significant. These results indicate that the PCR has a significant negative and asymmetric effect on the future realized volatility of SSE50 index returns. When the PCR is below its long-term average, the smaller the PCR is, the larger the stock (index) volatility will be. But this pattern does not hold when the PCR is above the average. In other words, more open interests of call options relative to the put options signal higher volatility in the stock market, but the open interests of the put options do not seem to play a role in any direction.

Because daily PCR may be noisy, we also use the past average PCR in the last 1 week, last 1 month and 3 months for robust tests. Results are reported in Table 7. Table 7 shows that the lower past average PCR in the last 1 week is still significant in 5-day and 20-day realized volatility. However, the past average PCR in the last 1 month and 3 months have less predictive power.

In addition, after controlling for the moneyness and time to expiration as shown by Table 8, the PCRs from the at-the-money options seem to be very informative (Panel A). This

† In addition, the prediction power has also been tested for longer horizons up to 20 days ($\tau = 1, 2, \ldots, 20$). The PCR is insignificant at any τ. Results can be obtained by request.

Table 6. Results of regressions of SSE50 index volatility on SSE50-ETF options PCR.

Regression	Constant	PCR_{lower}	PCR_{upper}	$R2$
5-day volatility	0.88 (5.26)***	−14.58 (−3.86)***	−0.22 (−0.11)	0.338
20-day volatility	1.08 (2.19)**	−11.49 (−3.35)***	−1.41 (−0.37)	0.294
60-day volatility	1.28 (1.78)*	−6.96 (−1.67)*	−3.94 (−0.58)	0.194

Notes: This table reports the results of regressions of SSE50 index volatility on SSE50-ETF option PCRs. 5-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+5$. 20-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+20$. 60-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+60$. $PCR_{upper} = \max(PCR\text{-}\mu_{PCR}, 0)$ and $PCR_{lower} = \min(PCR\text{-}\mu_{PCR}, 0)$, where μ_{PCR} is the sample mean of PCR. t-statistics reported in parentheses are computed by Newey-West methods corrected for autocorrelation and heteroscedasticity. One, two and three asterisks (*) respectively indicate the t-values are significant at the 0.1, 0.05 and 0.01 level.

Table 7. Results of regressions of SSE50 index volatility on SSE50-ETF options past average PCR.

Regression	Constant	PCR_{lower}	PCR_{upper}	$R2$
Panel A: Past average PCR in last 1 week				
5-day volatility	0.87 (3.64)***	−14.25 (−3.01)***	−0.63 (−0.22)	0.314
20-day volatility	1.07 (1.59)	−11.47 (−2.04)**	−1.99 (−0.32)	0.312
60-day volatility	1.21 (2.04)**	−7.55 (−1.44)	−3.88 (−0.54)	0.229
Panel B: Past average PCR in last 1 month				
5-day volatility	1.00 (3.73)***	−11.99 (−3.45)***	−3.18 (−0.74)	0.230
20-day volatility	1.12 (1.34)	−11.43 (−0.89)	−3.92 (−0.28)	0.291
60-day volatility	1.20 (2.13)*	−7.56 (−0.85)	−5.08 (−0.42)	0.251
Panel C: Past average PCR in last 3 month				
5-day volatility	0.92 (2.99)***	−11.71 (−1.80)*	−3.38 (−0.54)	0.250
20-day volatility	1.01 (0.57)	−11.60 (−0.34)	−3.76 (−0.10)	0.330
60-day volatility	0.96 (0.77)	−10.70 (−0.43)	−1.94 (−0.07)	0.399

Notes: This table reports the results of regressions of SSE50 index volatility on SSE50-ETF option past average PCRs. 5-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+5$. 20-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+20$. 60-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+60$. Past average PCR is calculated by the mean of PCR from day $t\text{–}\tau$ to day t, where τ is 5, 20 and 60 days respectively. $PCR_{upper} = \max(PCR\text{-}\mu_{PCR}, 0)$ and $PCR_{lower} = \min(PCR\text{-}\mu_{PCR}, 0)$, where μ_{PCR} is the sample mean of PCR. t-statistics reported in parentheses are computed by Newey-West methods corrected for autocorrelation and heteroscedasticity. One, two and three asterisks (*) respectively indicate the t-values are significant at the 0.1, 0.05 and 0.01 level.

Table 8. Results of regressions of SSE50 index volatility on SSE50-ETF options PCR by different option types.

Contract type	5-day volatility	20-day volatility		
	PCR_{lower}	PCR_{upper}	PCR_{lower}	PCR_{upper}
Panel A: Moneyness				
Above 10% OTM	−1.12 (−1.15)	−0.97 (−2.80)***	−0.71 (−0.80)	−1.06 (−2.93)
3–10% OTM	−3.81 (−2.05)**	−0.65 (−1.42)	−2.83 (−1.48)	−0.62 (−0.87)
Near-the-money	−5.14 (−3.56)***	5.68 (3.77)***	−6.13 (−3.33)***	5.61 (4.15)***
3–10% ITM	−0.01 (−0.03)	1.58 (2.41)**	−0.20 (−0.26)	1.17 (2.06)**
Above 10% ITM	1.50 (2.51)**	0.11 (0.20)	1.35 (2.21)**	0.09 (0.18)
Panel B: Time to expiration				
Under 40 days	−10.39 (−2.89)***	0.57 (1.60)	−8.25 (−2.91)***	0.90 (0.48)
40–99 days	−4.87 (−1.67)*	−3.49 (−2.08)**	−5.95 (−1.41)	−2.92 (−0.93)
Above 100 days	−14.30 (−3.90)***	1.91 (0.47)	−14.18 (−3.16)***	1.06 (0.17)

Notes: This table reports the results of regressions of SSE50 index volatility on SSE50-ETF option PCRs among varying moneyness and time to expiration. 5-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+5$. 20-day volatility is computed by the standard deviation of SSE50 index returns from day $t+1$ to day $t+20$. OTM denotes out-of-the-money options, and ITM denotes in-the-money options. Near-the-money refers to the call and put options having a strike to price ratio between 0.97 and 1.03. $PCR_{upper} = \max(PCR\text{-}\mu_{PCR}, 0)$ and $PCR_{lower} = \min(PCR\text{-}\mu_{PCR}, 0)$, where μ_{PCR} is the sample mean of PCR. T-statistics as reported in parentheses are computed by Newey-West methods corrected for autocorrelation and heteroscedasticity. One, two and three asterisks (*) respectively indicate the t-values are significant at the 0.1, 0.05 and 0.01 level.

is consistent with the fact that at-the-money options are the most actively traded, so they contain more information than the others. This very argument is the foundation of the VIX index as introduced by Whaley (1993), which is based only on (eight) at-the-money index calls and puts. But there are mixed results regarding time to expiration as suggested by Panel B of Table 8.

To further address the potential misspecification problem and control other effects in this univariate regression, we follow Chang *et al.* (2009) and introduce an interaction term

Table 9. Predictability from extremely low PCR in 5-day rolling window regressions with control variables.

	5-day volatility		20-day volatility	
	Coefficient	*t*-value	Coefficient	*t*-value
PCR $_{lower}$	− 9.61***	− 3.51	− 6.59*	− 1.84
PCR $_{upper}$	− 0.92	− 0.63	− 2.42	− 1.43
Dummy × near maturity PCR	0.15	0.62	− 0.11	− 0.57
Volume	0.009***	4.89	0.010***	3.57
$R_{-5,-1}$	− 0.030	− 1.26	− 0.015	− 0.73

Notes: This table reports the results of regressing next-5-day volatility of SSE50 index returns on SSE50-ETF option with three control variables: expiration dummy interacting with PCR, the daily closing trading volume of SSE50 index, and the five-day accumulated SSE50 index returns. Trading volume of SSE50 index is in billions. The *t*-statistics reported in parentheses are computed by Newey-West methods corrected for autocorrelation and heteroscedasticity. One, two and three asterisks (*) respectively indicate the t-values are significant at the 0.1, 0.05 and 0.01 level.

Table 10. Asymmetric VARX-MGARCH model estimation results.

	Coefficient	*t*-value
Mean equation		
Γ_{11}	− 0.188**	− 2.201
Γ_{12}	0.210***	2.650
γ_1	0.356*	1.953
δ_1	− 0.022	− 0.461
η_1	0.422	0.497
θ_1	0.788	0.469
Γ_{21}	0.045	0.463
Γ_{22}	− 0.057	− 0.637
γ_2	0.250	1.199
δ_2	− 0.084	− 1.584
η_2	0.631	0.662
θ_2	1.085	0.610
Variance Equation		
a_{11}	0.297***	8.334
a_{22}	0.278***	9.002
b_{11}	0.943***	77.560
b_{22}	0.948***	98.300
f_{11}	− 0.120	− 0.965
f_{12}	− 0.072	− 1.203
g_{11}	0.790***	5.635
g_{12}	1.274***	4.774
f_{21}	− 0.026	− 0.196
f_{22}	− 0.011	− 0.177
g_{21}	0.891***	5.939
g_{22}	1.345***	4.825

Notes: This table reports the results of Asymmetric VARX-MGARCH Model. *t*-statistics are computed based on robust standard errors (sandwich formula). One, two and three asterisks (*) respectively indicate the *t*-values are significant at the 0.1, 0.05 and 0.01 level. To conserve the space, some less relevant parameter estimates (e.g. the constant) are omitted.

between a dummy variable and the near-maturity PCR as the maturity control. The dummy variable takes the value 1 if there are one or more options about to expire on the next trading day. Otherwise, it takes the value 0. The near-maturity PCR is then calculated by options that will expire in the next trading day. For liquidity control, we add in the daily SSE50 index trading volume. For reversal control, we add in the past five-day SSE50 index cumulative return $R_{-5,-1}$. Table 9 shows the regressions of the 5-day and 20-day SSE50 return volatilities on the PCR and other control variables. It suggests similar results to Table 5 that only the PCR_{lower} matters and the relationship is negative. Hence, Table 9 suggests the robustness of this relationship that the time series of daily PCRs can signal the future realized volatility of the SSE50 index returns (negative and asymmetric). But such a trading implication towards the stock market using the PCR could also interact with other derivatives markets, especially those with identical underlying assets. This motivates us to investigate more across different markets that may be related to the PCR.

4.3. *Asymmetric VARX-MGARCH model*

Results, as shown above, have revealed the significance and direction of the PCR to forecast the future realized volatility of the stock market. However, in addition to the stock market and option market, there is an index futures market with the same underlying asset (IH futures) in China. Compared with the SSE50-ETF options, the index futures have a much longer history in China and therefore are more commonly used to hedge stock market risk. Therefore, to further examine the information in the PCR and the co-movements across different markets with the same underlying asset, we construct an asymmetric bivariate VARX-MGARCH model. Again, we separate the PCR into upper and lower parts to address possible asymmetric effect. We also separate the basis into positive and negative parts to take account of the asymmetric effects of lagged basis due to the short sale constraint of stocks in China as documented by Yang *et al.* (2012). Both the basis and PCR are treated as independent variables and included in the conditional mean and variance functions. We construct an optimal bivariate VARX(1)† model as the conditional mean function, with the time series of daily returns of the index futures and spot index as the dependent vector, and other variables as independent variables. We construct a multivariate GARCH(1,1) model as the conditional variance function. Table 10 summarizes the estimates, confirming the existence of the GARCH effects in both time series (daily

† The lag order of VAR is determined based on the BIC.

Table 11. Robustness check.

	First		Second	
	Coefficient	*t*-value	Coefficient	*t*-value
Mean Equation				
Γ_{11}	− 0.287***	− 3.260	− 0.246***	− 2.998
Γ_{12}	0.304***	3.520	0.264***	3.320
γ_1	0.351	1.348	0.359	1.433
δ_1	0.000	0.003	− 0.001	− 0.011
η_1	0.303	0.341	0.273	0.295
θ_1	0.870	0.498	1.024	0.598
Γ_{21}	− 0.068	− 0.708	− 0.010	− 0.108
Γ_{22}	0.056	0.586	− 0.003	− 0.029
γ_2	0.158	0.522	0.189	0.635
δ_2	− 0.130*	− 1.715	− 0.101	− 1.484
η_2	0.575	0.576	0.621	0.602
θ_2	1.056	0.571	1.186	0.648
Variance Equation				
a_{11}	0.289***	7.242	0.294***	7.031
a_{22}	0.283***	8.538	0.280***	7.991
b_{11}	0.948***	70.220	0.943***	65.510
b_{22}	0.948***	81.050	0.949***	81.700
f_{11}	0.174	1.319	0.219	1.302
f_{12}	0.140*	1.742	0.148*	1.955
g_{11}	0.722***	5.621	0.817***	5.306
g_{12}	1.064***	3.446	1.264***	4.606
f_{21}	0.090	0.626	0.122	0.661
f_{22}	0.091	1.083	0.088	1.148
g_{21}	0.856***	5.310	0.894***	5.193
g_{22}	1.240***	3.579	1.270***	3.853

Notes: This table reports the results of robustness check. *t*-statistics are computed based on robust standard errors (sandwich formula). One, two and three asterisks (*) respectively indicate the t-values are significant at the 0.1, 0.05 and 0.01 level. To conserve the space, some less relevant parameter estimates (e.g. the constant) are omitted.

returns of the stock index and index futures), and illustrating all four coefficients (g_{11}, g_{12}, g_{21}, g_{22}) related to the PCR asymmetry are highly significant in the conditional variance function. These results prove the PCR is highly significant in forecasting the conditional variances of both markets and does so in an asymmetric way. Specifically, coefficient estimates in Table 10 suggest an asymmetric V-shaped curve in the relationship between the PCR and the conditional variances: The conditional variances of both markets (the stock and futures markets) increase when the PCR either goes up or goes down from its mean. This result can be explained by the market sentiment. Past literature shows that the PCR is a reflection of market sentiment (Simon and Wiggins 2001, Dennis and Mayhew 2002). Low PCRs usually indicate optimistic market sentiment while high PCRs indicate the opposite. These sentiment fluctuations can introduce additional 'sentiment risk' and hence cause stock prices to be even more volatile (Dumas *et al*. 2009).

In particular, because the values of g_{12} and g_{22} are larger than those of g_{11} and g_{21} (this is also robust and reinforced as suggested by Tables 11 and 12), the conditional variances are more sensitive to lower PCRs than higher ones (Figures 3 and 4). This further implies that smaller values of the PCR are forward-looking and they predict future wild swings in both the stock market and index futures market. This is consistent with the fact that the bearish condition in the Chinese stock market is much longer than otherwise (also documented by Yu *et al*. 2017). In contrast to the US stock market as shown by the dotted line in Figure 5 where the bullish pattern dominates, the Chinese stock market has much longer (and more frequent) bearish periods than bullish ones.† Because the momentum effect is much stronger during a bullish stock market while reversal dominates the bearish, the call options are very much needed to cover (or speculate) the upside, whilst investors tend to resort to index futures to hedge the downside. Therefore, put options are less often used.‡ This is also reinforced by Figure 2, which suggests the PCR stays below 0.5 most of the time. In addition, Table 10 suggests the basis plays no role either in the conditional mean or variance based on daily frequency (as the coefficients of η, θ, and f are all insignificant in Table 10). This is consistent with the studies by Kawaller *et al*. (1987) and Yang *et al*. (2012), which

† Nyberg (2013) shows that the average period of bull market is 37.17 months and the average period of bear market is 14.08 months in the US, while the corresponding counterparts in China are 15.25 and 14.14 months, respectively. Liu and Wang (2017) also find the Chinese stock market has 'crazy bull' and 'frequent and quick bear'.

‡ There is another reason for the index option to be even less used to hedge the downside risk: the index futures market in China has a much longer trading history (since April 2010), therefore it has a much larger trading volume (62.7 billion yuan of all index futures and 1.02 million yuan of index options as of the date on 28 September 2018), more tradable underlying indices (including SSE50), and is more widely participated. Hence, the index futures contracts are much often used for hedging than index options.

Table 12. Results of robustness check with control variables.

	Coefficient	t-value
Mean equation		
Γ_{11}	− 0.124	− 1.370
Γ_{12}	0.179**	2.275
γ_1	− 0.136	− 0.538
δ_1	0.080	1.336
η_1	0.093	0.095
θ_1	2.984*	1.722
Dummy × near maturity PCR-1	− 0.470**	− 1.994
$R_{-5,-1}$-1	− 0.057***	− 3.283
Volume-1	0.007***	2.600
Γ_{21}	0.112	1.086
Γ_{22}	− 0.092	− 1.012
γ_2	− 0.263	− 0.916
δ_2	− 0.026	− 0.387
η_2	0.273	0.244
θ_2	3.325*	1.760
Dummy × near maturity PCR-2	− 0.478*	− 1.907
$R_{-5,-1}$-2	− 0.052***	− 2.782
Volume-2	0.007**	2.193
Variance Equation		
a_{11}	0.306***	8.157
a_{22}	0.283***	8.591
b_{11}	0.931***	54.850
b_{22}	0.938***	68.460
f_{11}	0.085	0.579
f_{12}	− 0.069	− 1.077
g_{11}	− 0.343	− 0.893
g_{12}	1.003**	2.249
Dummy × near maturity PCR-1	0.181	0.762
$R_{-5,-1}$-1	0.049	0.254
Volume-1	− 0.036***	− 2.852
f_{21}	− 0.042	− 0.271
f_{22}	0.014	0.202
g_{21}	− 0.398	− 0.905
g_{22}	1.074**	2.207
Dummy × near maturity PCR-2	0.093	0.512
$R_{-5,-1}$-2	0.051	0.253
Volume-2	− 0.039***	− 2.940

Notes: This table reports the results of robustness check. t-statistics are computed based on robust standard errors (sandwich formula). One, two and three asterisks (*) respectively indicate the t-values are significant at the 0.1, 0.05 and 0.01 level. To conserve the space, some less relevant parameter estimates (e.g. the constant) are omitted.

argue that the basis is important for the futures price to adjust toward a long-term equilibrium on intraday.

Furthermore, to show the volatility linkage between the two markets, a time-varying conditional correlation is calculated and plotted in Figure 6. The high correlation across the two markets indicates an intensive co-movement. These findings are consistent with earlier studies (e.g. Chan *et al*. 1991, Yang *et al*. 2012). Figure 6 also suggests a large drop starting around mid-2015, which is consistent with a dramatic stock market correction, and especially with many strict restrictions on the index futures market† during that time.

Tables 10–12 all confirm η and θ, which stand for possible asymmetric effects of the PCR on the conditional mean, to be statistically insignificant. This supports our initial results that the PCR cannot reliably predict the direction of the stock index on a daily basis, and is then consistent with the results in Table 4.

4.4. Robustness check of the VARX-MGARCH

To check the robustness of our model, we first reconstruct various calculations of the continuous futures price series and re-estimate the VARX-MGARCH model. We adopt two different methods: (1) The method of McMillan and Speight (2006): The nearest-to-maturity contract is always used, and switching to the next-nearest contract when the trading volume in the second-nearest contract exceeds that in the nearest-to-maturity contract; (2) The method of Chen and Gau (2010): The most actively traded nearest-to-maturity contract is used, and switching to the next-nearest contract five days before the expiration date. Both methods can avoid expiration effects. Yang *et al*. (2012) also adopt these two methods to check the robustness. Table 11 summarizes the estimates of the VARX-MGARCH models based on the newly constructed price series. In addition, two new plots of the dynamic conditional correlations are shown in Figure 7. All these robustness checks are consistent with our results as in Table 8.

Second, we then introduce three control variables to the VARX-MGARCH system. Following Chang *et al*. (2009), we add a maturity control, defined as an interaction term between a dummy variable and the near-maturity PCR. The dummy variable takes the value 1 if there are one or more options about to expire on the next trading day; otherwise, it is 0. We calculate the near-maturity PCR from the options that will expire on the next trading day. For liquidity control, we choose the daily trading volume of the SSE50 index. For reversal and momentum control, we add in the past five-day SSE50 cumulative return, $R_{-5,-1}$. Table 12 shows the model estimation with the above control variables. Coefficient estimates suggest the robustness of the PCR asymmetry in the conditional variance equation that the PCR matters only when they are lower than its long-term average (by observing that only g_{12} and g_{22} are significantly positive). Table 12 also

† During the market crash, there are many critics of the role of index futures arguing that the index futures market serves as a venue of speculative trading and exacerbates the spot market volatility. Therefore, the China Financial Futures Exchange (CFFEX) announced on August 25 that starting August 26, three measures would be adopted to curb speculative trading in the index futures market. First, the initial margin for non-hedging trades would be raised from 10% to 12%, 15%, and finally 40% over the following two weeks. Second, any single day non-hedging trading of over 10 contracts would be considered abnormal trade and be subject to scrutiny. Third, the clearing fees for intraday trades would be adjusted upward to 1.15 (soon adjusted to 23) basis points. With these drastic measures, the index futures trading in China nearly came to a complete stop (Han and Liang 2017).

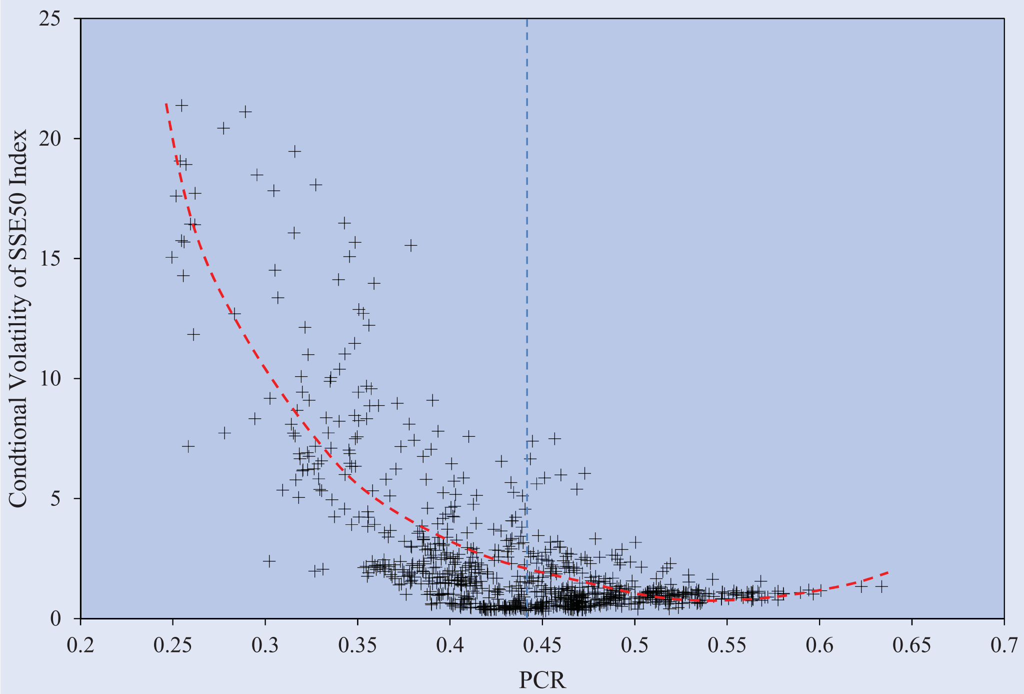

Figure 3. Relationship between PCRs and the SSE50 index conditional volatility.

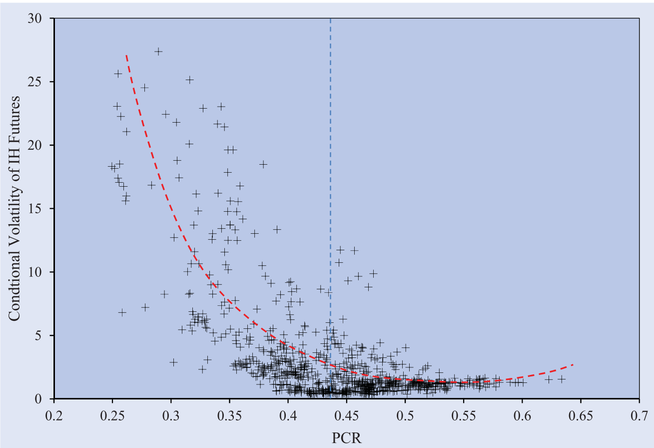

Figure 4. Relationship between PCRs and the IH futures conditional volatility.

shows that the trading volume of the SSE50 index plays a role in reducing the conditional variance of both markets.

5. Conclusions

This paper investigates the role of the put-call-ratio (PCR) implied by the SSE50-ETF option in forecasting the SSE-50 index and its futures. Empirical evidence indicates that the PCR predicts the future realized volatility of the SSE50 return, but can less reliably predict the SSE50 return. By using univariate and multivariate models, we find no evidence that the daily PCRs of SSE50-ETF options can predict any direction of movement in the SSE50 index. These results are highly robust but differ from the past literature, and hence suggest a possible past misuse of the PCR in predicting the SSE-50

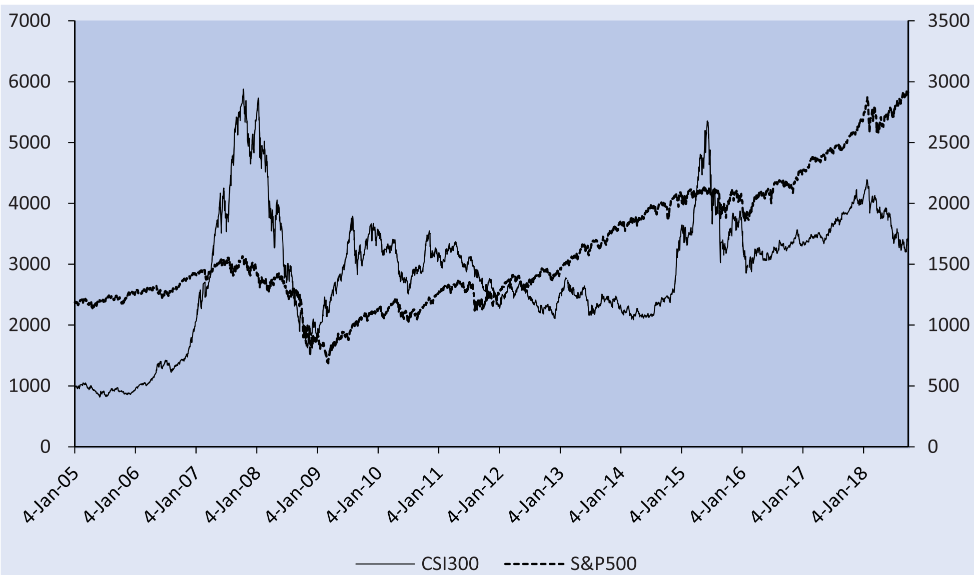

Figure 5. CSI300 and S&P500 index prices.

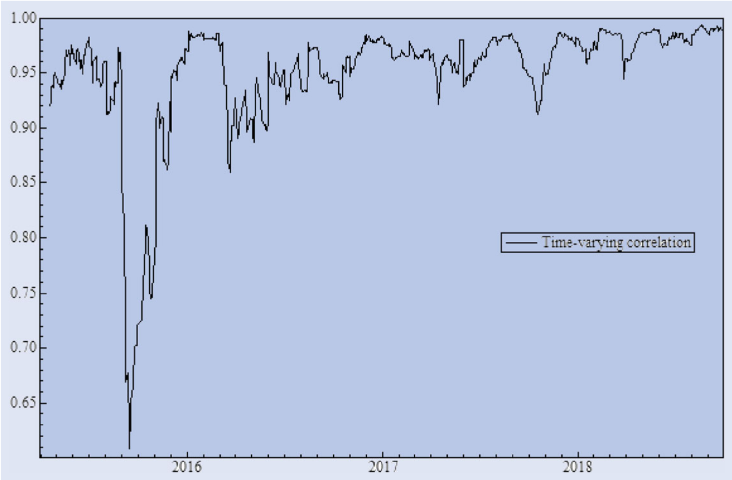

Figure 6. Time-varying correlations across markets. Note: The time-varying conditional correlation is computed as to gauge the volatility linkage across the spot and futures markets, where h11t and h22t are conditional variance of spot market and futures market, and h12t is conditional covariance of the two.

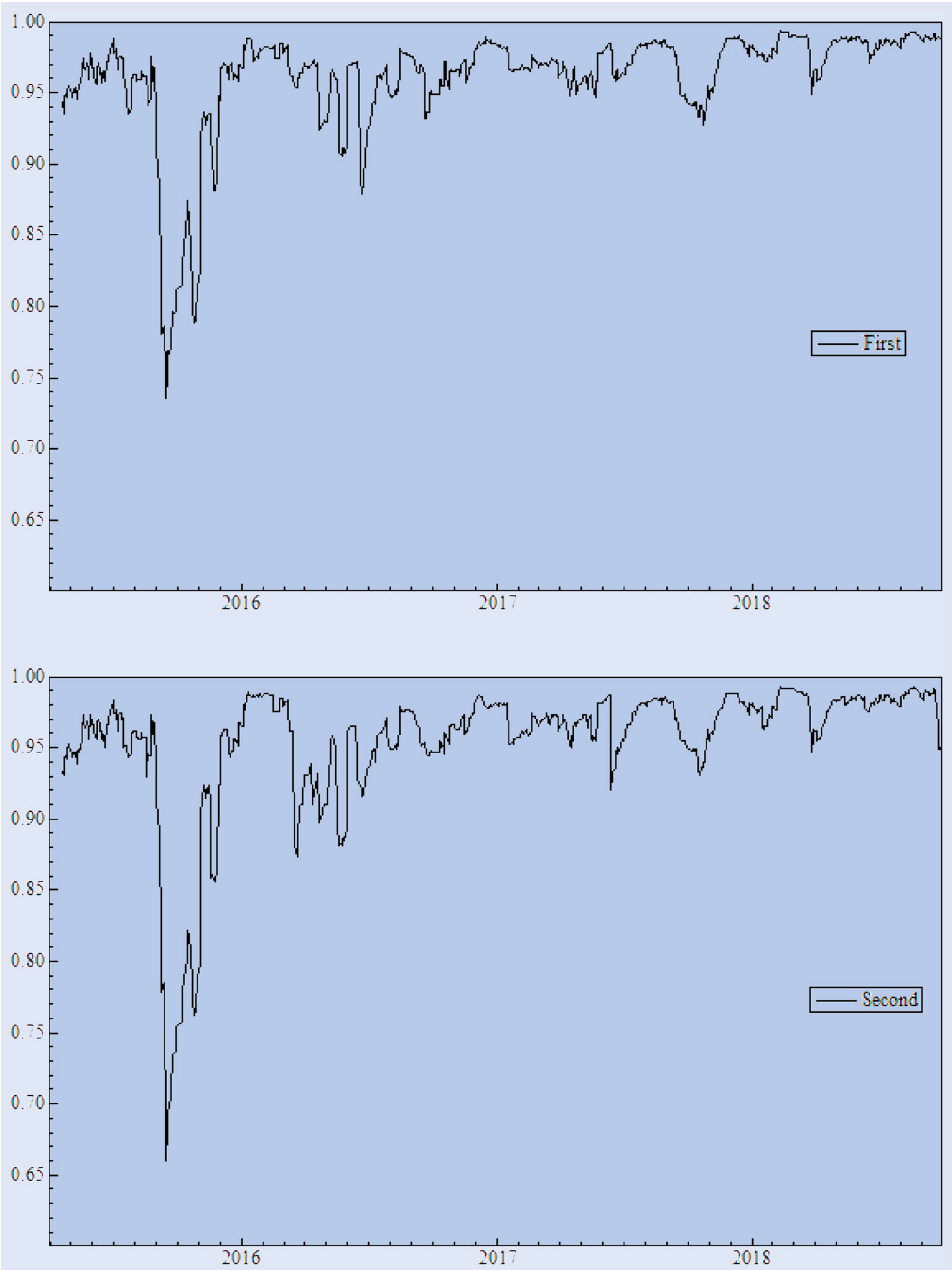

Figure 7. Robustness check: time-varying correlation across markets.

index return. Our results are also reinforced by detailed work on various control variables such as moneyness, maturity, etc.

This study also documents a robust, negative, and asymmetric relationship between the PCR and the conditional variance of both stock index and index futures returns under a VARX-MGARCH model. Evidence shows that the PCR does significantly forecast the conditional variances but in an asymmetric way. Specifically, coefficient estimates suggest an asymmetric V-shaped curve: The conditional variances of the spot index and index futures returns both increase when the PCR either goes up or goes down from its long-term average, but the effects are more dramatic when the PCR goes down. These results imply that PCRs that significantly deviate from their long-term average are informative, and they predict future swings in both the stock market and the futures market. Furthermore, low PCRs are more informative than high ones. Our results are robust to moneyness, trading volumes, and different methods of building continuous futures price series.

To conclude, this study is among the very first to be focused on the PCR of SSE50-ETF options. Our results show different results from the past literature relating to exploiting information from trading behaviors. Our research indicates the wide misuse of the PCR as an indicator in the Chinese financial markets, and, instead, provides a correct way of using it: to trade on the volatility.

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