Time-varying price discovery in spot, futures and options markets: Evidence from China

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Abstract

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This paper analyzes the time-varying price discovery roles of the spot, futures and options markets, represented by three products based on the SSE50 Index using high frequency data from April 2015 to July 2017. This sample is particularly interesting in that (1) it spans the period immediately after the launches of the options and futures, which enables us to evaluate the development course of the derivatives markets, and (2) the Chinese financial markets have meanwhile undergone dramatic fluctuations and abrupt regulation changes. After identifying two structural breaks in the sample period, we estimate time-varying strength of price discovery roles among spot, futures and options markets. We find that the derivatives markets in China soon started playing a dominant role in the price discovery despite their short history. The leading price discovery role of the spot market quickly declined after the launch of the two derivatives. The contributions of the futures market have been considerably large since their launch, while those of the options market was mediocre in the beginning but recently becomes dominant. In case of a bivariate, rather than trivariate, analysis with a single derivative and its underlying spot markets, the role of the derivative is overstated, which confirms the importance of joint examination of the three markets. This paper also explores the determinants of the time varying price discovery ability of derivatives. We find that substantial changes in futures transaction costs do not lead to significant changes in price discovery, which is inconsistent with the trading cost hypothesis. We provide a potential explanation.

Keywords: Price discovery, Chinese derivatives markets, Trading cost hypothesis, Trivariate VECM

JEL Classification: G13, G14

1 Introduction

The stock markets in China have achieved rapid development and recently became the second biggest following the US stock markets in terms of the market capitalization,[1] but its derivative markets are still in an infant stage. In 2010, the first stock index futures (CSI300 Index futures) was launched in the China Financial Futures Exchange (CFFEX). In early 2015, the Shanghai Stock Exchange (SSE) introduced the very first exchange-traded stock options (SSE50 ETF options) and the CFFEX launched the second index futures (SSE50 Index futures), which marked the advent of a new derivative era in China.

The introduction of futures and options greatly makes up the limitations of trading mechanism in the current Chinese stock markets in several aspects. First, the derivatives virtually enable short-selling, which is severely limited in the underlying spot market. Second, the derivatives are traded based on the "T+0" settlement system. In contrast, regulators have adopted the "T+1" settlement system in the spot market since early 1995 to prevent the excessive speculation and potential flash crash events. Since the "T+1" system could aggravate trend-chasing trading behavior, the "T+0" system in the derivatives markets can make information transmission more efficient. Third, instead of the traditional continuous auction systems, the options market adopts the market-making system, which is expected to provide sufficient liquidity to the market. In theory, all of these aspects are conducive to enhancing the market quality (Subrahmanyam, 1991; Gorton and Pennacchi, 1993).

A large number of studies have documented the price discovery role between a single derivative (either futures or options) market and its underlying spot market, and show that the derivative market responds faster to the arrival of new information due to lower transaction costs and the lack of short-sale restrictions (Chan, 1992; Iihara et al., 1996; Tse, 1999; So and Tse, 2004; Chakravarty et al., 2004; Chou and Chung, 2006; Chen and Chung, 2012), but relatively few papers have jointly considered the spot, futures and options

[1] As of October 31, 2017, the market capitalization of the New York Stock Exchange and the NASDAQ is USD 21,377 billions and USD 9,585 billions, respectively, while the Shanghai (Shenzhen) Stock Exchange has the market capitalization of USD 5,043 (3,688) billions.

markets, particularly in emerging countries.[2] If both futures and options are actively traded but we only consider a bivariate relationship between a single derivative market and its underlying spot market, then the estimated price discovery role can be biased because of the omitted variable. Since it is not likely that the role of the omitted market is exactly proportionally allocated to the other markets, the bivariate analysis can be misleading. Not only does this paper fill the research gap between developed and developing markets by using high frequency Chinese data, but also it estimates the relative strength in price discovery in the spot, futures and options markets without potential bias by jointly analyzing the three cointegrated markets.

Compared to the data used in previous studies, the sample in this paper is particularly interesting and valuable for two reasons. First, the sample spans the period immediately after the launches of the derivatives, which enables us to evaluate the development course of the derivatives markets. Unlike a mature and developed derivative market, a nascent derivative market particularly in an emerging country may not necessarily play its supposed price discovery role (Yang et al., 2012; Sohn and Zhang, 2017). From this sample, we can learn how long it takes for nascent derivatives markets to function properly and what determines the strength of price discovery. Second and more importantly, the Chinese derivatives markets have undergone dramatic up and down swings and abrupt changes in regulations during this sample period. The transaction cost for futures trading was 0.0025% of the settlement amount at first, slid slightly to 0.0023%, rose five times to 0.0115%, skyrocketed 20 times to 0.23%, and then declined again to 0.092%. Meanwhile, the option trading cost dropped by 35% from 0.02% to 0.013% of the transaction amount. The literature has shown numerous evidence that supports the trading cost hypothesis (Fleming et al., 1996; de Jong and Donders, 1998; Booth et al., 1999; Hsieh et al., 2008). In other words, the dominant price discovery role in the derivatives markets is attributed to their relatively lower transaction

[2] Fleming et al. (1996) and Booth et al. (1999) are two of a few papers that jointly examine the relative price discovery roles in the spot, futures and options markets. Their data are from developed markets (the US or Germany) and the sample periods begin after several years since the launches of the derivatives markets.

cost. This sample period enables us to test this hypothesis because substantial and almost exogenous changes in the transaction cost occurred within a couple of years.

This paper first overviews the institutional facts about the launches of the SSE50 ETF options and the SSE50 Index futures, and discusses their development over the two years. By using the recursive Chow tests, two structural breaks are detected in the sample period. The two identified structural breaks turn out to well coincide with the major regulation changes. Next, we construct the comprehensive measures of the price discovery ability in the spot, futures and options markets, and investigate how they evolve over time. Specifically, we use SSE50 ETF, SSE50 Index futures and SSE50 ETF options to represent the spot, futures and options market, respectively, and then quantify the price discovery ability by Gonzalo and Granger (1995)'s common factor weights and Hasbrouck (1995)'s information shares, both of which are based on a cointegration relationship. We also consider the gross and net spillover of each market by decomposing the forecast error variance attributed to innovations in each market (Pesaran and Shin, 1998; Diebold and Yilmaz, 2012). Instead of a parametric specification of the time-varying price discovery ability, we estimate the VECM on a daily basis using the intraday data to learn its fluctuations as in Hasbrouck (2003) and several others.

We find that although the Chinese derivatives markets have only a few years of trading history, they soon start playing a dominant role in the price discovery. In the overall sample, the information share of the futures (options) market is 34.03% (41.49%). The results show that the leading price discovery role of the spot market quickly declines after the launch of the two derivatives. In the first subsample, the information share of the spot market is 40.16%, but in the last subsample, it is only 15.40%. The information share of the futures market has been considerably large since the launch (37.54% in the first subsample; 30.17% in the last), while the information share of the options market is mediocre in the first subsample (22.30%) but steadily increasing and becomes dominant in the last subsample (54.43%). The results are robust when the price discovery is measured by the common factor weights and the net spillover effects.

We also show that the bivariate analysis overestimate the price discovery role of the derivative products. When we consider a bivariate relationship between spot and futures markets, the estimated information share in the futures market is 67.42%. For the same analysis with spot and options data, the options market takes 67.76% of the information share. In other words, given that both futures and options markets exhibit superior price discovery ability to the underlying spot market, the contribution of the omitted derivative market is subsumed mostly by the included derivative market. This tendency is more pronounced recently when both derivatives are actively traded. This finding reveals a possibility of potential bias in the previous literature in which only two markets, out of other actively traded markets, are analyzed.

Finally, this paper explores the factors that affect the time variation in price discovery ability of derivatives. The results show that in the options market, the price discovery role is positively correlated with the trading volume and the open interests, and negatively correlated to the volatility, which is consistent with the literature (Chakravarty et al., 2004; Chen and Chung, 2012). In the futures market, however, the trading volume does not significantly covary with the magnitude of price discovery. Even with more than 90% plunge in trading volume after stringent regulations and raised transaction costs, the futures market still make considerable contributions to price discovery. Its information share, common factor weights and net spillovers did not significantly decreased after the regulation. This finding is not consistent with the trading cost hypothesis. We conjecture that the trading experience of investors, rather than the transaction cost, matters more for the price discovery role in a nascent market. When the SSE50 Index futures was launched, the futures investors had already accumulated five-year trading experiences since the introduction of the first index futures (CSI300 Index futures). In contrast, the SSE50 ETF options were the very first exchange-traded options and investors needed time to familiarize themselves with the new financial instrument. This result provides a novel implication about the strength of price discovery. In a nascent market, the price discovery ability in a market does not necessarily depends on transaction costs but on whether investors are mature and experienced sufficiently.

The rest of the paper continues as follows. Section 2 briefly describes the background of the spot, futures and option products commonly based on the SSE50 Index. Section 3 explains the data construction process and the structural breaks in the sample period. In Section 4, we present the methodology to measure the price discovery ability of the three markets, and discuss the findings. Section 5 concludes the study.

2 Institutional Background

The SSE created the SSE50 Index on January 2, 2004, which picks up the 50 largest and most liquid A-share stocks listed on the SSE. This index aims to reflect the overall performance of the most influential blue-chip Shanghai stocks. Its constituent stocks account for more than 28% of the A-shares market capitalization. On February 23, 2005, the SSE launched the first exchange-traded fund (ETF) in China, called SSE50 ETF, which is now one of the largest and most liquid ETFs in China. The ETF's stock portfolio is constructed according to the constituent stocks of the underlying SSE50 Index and its corresponding weights.

After ten years since the launch of the ETF, the SSE introduced the SSE50 ETF options on February 9, 2015, which is the first exchange-traded options in China. The SSE chose the SSE50 ETF as the underlying asset for two purposes. First, the SSE intended to lead investors' interest towards large-cap stocks, reducing their exposure to higher risk of small-cap stocks, for which Chinese individual investors tend to trade. Second, the SSE50 ETF is difficult to manipulate thanks to its high liquidity and trading volume, which can alleviate investors' potential distrust of the very first exchange-traded option.[3]

The SSE50 ETF options market adopts the market maker mechanism, which requires market makers to provide liquidity by maintaining bilateral quotes. The SSE organizes ten

[3] See Appendix A for the details of the SSE50 ETF options.

market makers and the orders are executed by the principle of price/time priority. The market maker mechanism is helpful in keeping the bid-ask spread narrow, enhancing the market transaction rate, and meeting the immediate transaction needs of investors by providing liquidity. These roles are particularly important in the nascent options market in China because the trading volume of deeply out-of-the-money contracts could be relatively small and a consequent possibility of pricing bias is big concern for investors. Under the market maker mechanism, the market maker provides the bilateral quotation for the market in real time, which alleviates the mispricing concern.

The entry barrier of the SSE50 ETF options trading is set high not only through the capital requirement (at least CNY500,000; approximately, USD78,000) for individual investors but also through the strict qualification demand for investors' professional knowledge. Specifically, the participants in the options market are required to pass qualification tests and according to the test level, investors can start options trading for the pre-defined purposes.[4] As a result, the microstructure of the options market is relatively well balanced compared to the spot market, in which less sophisticated individual investors dominate. According to the recent statistics from the SSE, individual investors contribute 43.29% of trading volume, while institution investors' trading volume amount to 56.71% in the options market. These figures are in contrast to the XX% of institutional investors' trading volume in the spot market. Therefore, one can expect that there are more informed and professional investors in the options market, which is supposedly conducive to faster information transmission and price discovery in the market.

Following the first introduction of the index futures in China in 2005 (CSI300 Index futures), the China Financial Futures Exchanges (CFFEX) introduced two additional index futures, SSE50 Index futures and CSI500 Index futures on April 16, 2015. These two new futures contracts aim to complement the existing CSI300 Index futures and provide more

[4]Investors who pass the level 1 test are allowed to trade options to hedge existing underlying holdings. Level 2 investors are allowed to take long positions for non-hedging purpose, while level 3 investors have full rights for both long and short options trading.

investment instruments and risk management tools for asset allocation.[5]

In September 2015, the China Securities Regulatory Commission (CSRC) attributed the traders in China's stock index futures market to one of the reasons for the stock market crash, and began to strictly control the trading activities. First, the CSRC limited the daily open positions for each type of stock index futures to ten contracts. Second, it tightened the margin requirements of the index futures, so that the margin for non-hedging positions increased from 30% to 40% of the contract value, whilst that for the hedging positions increased from 10% to 20% of the contract value. Third, the commission fees for intraday position closing increased from 0.0115 percent to 0.23 percent of the transaction volume. Indeed, it was since late August that the CSRC started imposing a series of regulations on the index futures market. The non-hedging transactions margin increased from 10% to 12% on August 26, to 15% on August 27, to 20% on August 28, and to 30% on August 31. The regulators tried to curb speculations and stabilize the capital market through tightening the stock index futures market. The trading volume in China's stock index futures plunged approximately 99% after the announcement of the strict regulations from the CSRC. The market liquidity was seriously affected, which could possibly affect the price discovery in the futures market. The details of futures trading activities are addressed in the following section.

3 Data

3.1 Price Time Series

This section describes how to construct the price time series in the spot, futures and options markets. The sample spans the period from April 16, 2015 to July 20, 2017 and is obtained from the WIND Financial Terminal. Previous studies have used various data frequency. Manaster and Rendleman Jr. (1982) analyze daily closed spot and option prices, while rel-

[5]See Appendix A for the details of the SSE50 Index futures.

atively recent papers by Stephan and Whaley (1990) and Fleming et al. (1996) use higher frequency 5-minute and 1-minute price observations, respectively. Nowadays most exchanges adopt electronic trading and the cost of transactions has been reduced. Consequently, the trading volume has significantly increased and information transmission is presumably much faster. To better estimate the extent of price discovery in each market, the high frequency data are desirable. In addition, in the empirical analysis, higher frequency data make the correlations among inter-market residuals smaller, which enables us to construct more precise information share measures. Hence, we use 1-minute frequency observations of closed prices from the spot, futures and options markets.

SSE50 ETF is used to represent SSE50 Index. Because not all securities can be traded at the same time, the index level recorded every minute may not be a perfect reflection of information regarding the constituent stocks' equilibrium value, while SSE50 ETF is less subject to the nonsynchronous trading problem addressed in Scholes and Williams (1977). We call the price of SSE50 ETF the *spot price* in this paper.

Unlike the spot price, the time series of futures and option prices are not readily available because there are multiple simultaneously traded contracts with different expiration dates. We construct a single price time series for each derivative as follows. Among the four futures contracts with the different expiration dates, we choose the one with the largest trading volume each day. We construct the data in this way because the most frequently traded contract has the largest liquidity and supposedly contains the most information. In general, the most nearby contract has the largest trading volume except for several days before the expiration date. The futures prices are then scaled down to make them comparable to the prices of SSE50 ETF. Specifically, we use the one-thousandth of the SSE50 index futures price, which we call the *futures price* in this paper.

The similar method is adopted to construct a single price time series in the options market. Among various simultaneously traded options with different expiration dates and strike prices, we choose the most nearby at-the-money pair of call and put options. At-the-money options are defined as the options whose strike prices are within 2.5% of the underlying spot price. To avoid the well-documented variability several days before the expired date, the next month contract replaces the expiring one when there are nine trading days left to maturity as in Booth et al. (1999). If there are multiple pairs of call and put options that have strike prices within 2.5% of the spot price, we choose the pair with the largest trading volume.[6] Using this pair of at-the-money call and put options, we recover the implied spot price by the put-call parity:

$$O_t = C_{t,T} - P_{t,T} + Ke^{-r(T-t)}, \tag{1}$$

where $C_{t,T}(P_{t,T})$ is the call (put) option price at t with the expiration date T, K is the strike price, and r is the risk-free rate. O_t is the option-implied spot price, which we call the *option price* in this paper. Three-month Treasury Bills rate is used for the risk-free rate.

Compared with the Black and Scholes (1973)'s model, which suffers from the model misspecification risk and the burden of parameter estimation (Jiang and Tian, 2005), the put-call parity is only based on the law of one price and no friction assumption and does not depend on any asset-pricing model. In the liquid market, there is supposedly no arbitrage opportunity to earn profit from the divergence of the put and call options. The at-the-money options among the nearest month contracts is generally the most liquid ones. Therefore, a violation of put-call parity is the least likely for the at-the-money nearby option contracts. Indeed, the put-call parity has been used as an alternative to the Black-Scholes model in the literature (Kang et al., 2006; Hsieh et al., 2008).

[6] The empirical results are robust to how the time series are constructed. For example, the conclusion remains qualitatively unchanged when the price time series of futures and option are defined based on open interests rather than trading volume.

3.2 Structural Breaks

Figure 1 plots the price time series obtained in Section 3.1: log prices (Panel A) and log bases (Panel B). The log futures (option) basis is defined as the difference between the log spot price and the log futures (option) price. Panel C shows the daily standard deviation of 1-minute returns in each market. The figures show that during the sample period, China's capital market experienced dramatic fluctuations. After the peak in the middle of June 2015, the bubble began to burst. In just one month, the stock market lost approximately 30% of its value. Since the dominant players in the market are individual investors, the Chinese government tried to stabilize the market and to limit investors' losses, curbing the expansion of systemic risk. Table 1 presents the list of major regulations in the derivatives markets during the sample period. After several months of calm periods since the strict serial regulations, however, the stock market fell into another crash in the beginning of 2016. In late February 2016, the market began to stabilize.

With both strong bull and bear markets, and calm and volatile periods in the sample, we suspect at least one structural break. To detect structural breaks, we use the recursive Chow tests. Ten variables are considered for the test: daily return volatility and trading volume from the three markets, and daily open interests and log basis volatility from the two derivative markets. Each variable is assumed to follow an autoregressive process. A Chow test is recursively conducted for each variable using the 60-day rolling windows. The null hypothesis is no structural break, while the alternative hypothesis is a break in the middle of the window. For each estimation window, we choose the optimal lag length of the autoregressive process by the Bayesian information criterion (BIC). A structural break is recorded on a day if the null is rejected for more than two-third of the considered variables. We record only one structural break within 60 trading days. If multiple breaks are detected within 60 trading days, the day with the most rejections of the null is recorded as a single break.

Table 2 shows the result of the recursive Chow tests. During the sample period, two structural breaks are detected: September 7, 2015 and November 1, 2016. These two points are well coincident with important regulation changes as shown in Table 1. The aforementioned restrictive regulations on the futures market came into effect on September 7, 2015. November 1, 2016 is the day after the announcement of promoting regulations on the options market. Specifically, the commission fees were reduced from 0.02% to 0.013% of the closed transaction amount. The detected structural breaks are generally consistent with Figures 1, 2 and 3. The trading volume in the spot and futures markets plummeted after September 7, 2015. The open interests in the futures market and return volatility in all three markets also dropped significantly, although their extent is not as notable as in trading volume. After November 1, 2016, trading volume and open interests in the derivative markets are significantly greater, while the return volatility is significantly reduced.

Based on these two structural break points, we divide the full sample into three subsamples and call them Period 1, 2 and 3. Table 3 presents the descriptive statistics for the overall sample and three subsamples and shows the significant differences among the subsamples. After the first subsample, which is the strong bear market with extreme volatility, the trading activities in the spot and futures markets are dramatically suppressed due to weak investor sentiment and strict regulations. In contrast, the options market trading grows steadily. In the third subsample, which is the period of steady and stable recovery, trading activities in the options market more than double, while those in the spot and futures markets almost stagnate.

4 Empirical Analyses

This section describes the methodology to analyze the extent to which the spot, futures and options markets contribute to price discovery. Then, we present the results and discuss their meanings.

4.1 Information Shares and Common Factor Weights

The price discovery ability of a market is usually measured by Hasbrouck (1995)'s information share (*IS*) and Gonzalo and Granger (1995)'s common factor weight (*CFW*). The *IS* of a market captures its contribution to the variance of innovations to the common factor. The *CFW* reflects each market's relative contribution to the common factor. These two measures are derived from a common cointegration relationship and have similarity, but they differ in that the *IS* incorporates the correlation between innovations of the three markets while the *CFW* does not. Therefore, the two measures provide complementary views of price discovery among the markets.

The analysis of the long-run price discovery implicitly assumes a cointegration relationship among the spot, futures and option prices. The plots in Figure 1 and the test results in Table 3 graphically and formally confirm the existence of a cointegration relationship among them over various sample periods. Table 3 presents the summary results of the daily cointegration tests. The Engle-Granger test assesses the null hypothesis of no cointegration among the log prices of the three markets. The Johansen test assesses the null hypothesis of cointegration rank equal to two against the alternative of three. In case of the full sample, the null of no cointegration is rejected in 516 trading days (93.14%) out of the total 554 trading days according to the Engle-Granger test. The Johansen test shows that the null hypothesis of the cointegration rank being equal to two cannot be rejected for more than 80% of the trading days. Even when the market was in turmoil (Period 1), 97.96% of the total trading days are indicated to have a cointegration relation by at least one of the tests. Based on these test results, this paper assumes the existence of a cointegration relationship with the cointegration rank of two.

Let $p_t = (s_t, f_t, o_t)'$ be a vector of log prices in the spot, futures, and options markets at time t, and let $\beta = \begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \end{bmatrix}'$ be the cointegrating matrix. As implied by the Johansen test, there are two cointegrating vectors: $(1, -1, 0)'$ and $(1, 0, -1)'$. The cointegration implies that the cointegration errors, the log futures basis $s_t - f_t$ and the log option basis $s_t - o_t$ in this case, should be stationary. In other words, the prices may temporarily deviate from one another, but they should share a common stochastic trend in the long run. A cointegration relationship is represented by the vector error correction model (VECM) as follows:[7]

$$\Delta p_t = \alpha\beta' p_{t-1} + \sum_{k=1}^{K} A_k \Delta p_{t-k} + \epsilon_t, \tag{2}$$

where α is the 3-by-2 error-correction coefficient matrix for the two cointegration error terms $\beta' p_{t-1}$ and measures how the prices react to the deviation from long-run equilibrium relationships. Its sign and magnitude represent the direction and speed of the error correction. K is the lag length of the model and is chosen by the BIC. A_k is the 3-by-3 autoregressive coefficient matrix, reflecting the effects of the short-term fluctuation on prices. ϵ_t is the 3-by-1 zero-mean vector of serially uncorrelated disturbances with covariance matrix Ω.

The *CFW* is obtained from Gonzalo and Granger (1995)'s permanent-transitory decomposition, in which the common permanent component is a linear combination of the cointegrated time series vector. They show that the weight for the linear combination is orthogonal to the error-correction coefficient vector. Specifically, the 3-by-1 weight vector is denoted by $\alpha_\perp = (\alpha_\perp^s, \alpha_\perp^f, \alpha_\perp^o)'$ and is defined such that $\alpha_\perp' \alpha = 0$. With the orthogonal component to the error-correction coefficient vector, the *CFW*s in the spot, futures and options markets is respectively defined as follows:

$$CFW_s = \frac{|\alpha_\perp^s|}{|\alpha_\perp^s| + |\alpha_\perp^f| + |\alpha_\perp^o|}, CFW_f = \frac{|\alpha_\perp^f|}{|\alpha_\perp^s| + |\alpha_\perp^f| + |\alpha_\perp^o|}, CFW_o = \frac{|\alpha_\perp^o|}{|\alpha_\perp^s| + |\alpha_\perp^f| + |\alpha_\perp^o|}.$$

Since $\alpha_\perp' p_t$ is the common permanent factor, the *CFW* indicates the contribution of each time series to the common efficient price.

The *IS* takes into account additional information of the innovation variances and covariances. By the Granger representation theorem, Equation (2) can be expressed as the

[7]A constant term does not affect the analysis and is omitted for notational simplicity.

VMA(∞) as follows:

$$\Delta p_t = \Psi(L)\epsilon_t, \tag{3}$$

where $\Psi(L) = \sum_{k=0}^{\infty} \Psi_k L^k$, Ψ_k is the 3-by-3 moving average coefficient matrix and L is the lag operator. The integrated form of VMA(∞) is expressed as:

$$p_t = \Psi(1) \sum_{s=1}^{t} \epsilon_s + \Psi^*(L)\epsilon_t, \tag{4}$$

where $\Psi^*(L)\epsilon_t$ is a zero-mean stationary process, representing the transient effect. $\Psi(1)$ is the sum of moving average coefficients and it turns out to be such that $\beta'\Psi(1) = 0$ due to the properties of cointegrated time series. Given $\beta' = \begin{bmatrix} 1 & -1 & 0 \\ 1 & 0 & -1 \end{bmatrix}$, all rows in $\Psi(1)$ should be identical. Denoting the common row as ψ, $\Psi(1) = \psi\iota$, where ι is a 3-by-1 vector of ones. Hasbrouck (1995) interprets the increment $\psi\epsilon_t$ as the common permanent impact of the shock at t into the prices, and calls it the common efficient price. The variance of the common efficient price is denoted as $Var(\psi\epsilon_t) = \psi\Omega\psi'$. Hasbrouck (1995) suggests a measure of the price discovery ability as the weight of the common factor variance. The greater proportion of the variance the innovations in a market constitute, the stronger price discovery capability the market possess. Formally, the *IS*s of the spot, futures and options markets are defined as follows:

$$IS_s = \frac{([\psi M]_1)^2}{\psi\Omega\psi'}, \quad IS_f = \frac{([\psi M]_2)^2}{\psi\Omega\psi'}, \quad IS_o = \frac{([\psi M]_3)^2}{\psi\Omega\psi'},$$

where M is a lower triangular matrix of the Cholesky factorization of Ω such that $\Omega = MM'$, and $[\psi M]_j$ is the j^{th} entry in ψM. Note that the *IS* is closely related to the ordering of state variables because of the nature of the Cholesky factorization. It maximizes (minimizes) the *IS* of the first-ordered (last-ordered) variable. In a bivariate analysis, the *IS* is commonly calculated as the midpoint of upper and lower bounds. Since this paper considers prices in the three markets, there are six possible permutations. We compute the *IS* of each market as the average value from the six permutations, which is the same calculation method as So and Tse (2004).

We obtain the *IS* and *CFW* each day using the intraday 1-minute frequency price observations.[8] Table 5 reports the mean and median of the daily *IS* and *CFW* of the three markets in the overall sample and the three subsamples. We find that these two measures are almost identical, which implies that the contemporaneous correlation among inter-market residuals is sufficiently small (Baillie et al., 2002). This could be due to the virtue of high frequency observations.

In the overall sample, the *IS*s (*CFW*s) of the spot, futures and options markets are, on average, 24.48% (23.14%), 34.03% (30.36%), and 41.49% (46.50%), respectively, which shows that the options market plays the dominant price discovery role. Throughout the subsamples, however, we observe substantial changes in the *IS* (*CFW*). When the futures and options markets were just launched (Period 1), the spot market mostly led the other markets with 40.16% of the *IS* (40.95% of the *CFW*). In contrast, the contribution of the options market was limited to approximately 20%. As the derivatives markets mature, the role of the spot market was taken over by the options market. The *IS* of the spot market is reduced to 24.85% in Period 2 and to 15.4% in Period 3. Meanwhile, the *IS* in the options market increases to 39.87% in Period 2 and to 54.43% in Period 3. Interestingly, the price discovery role of the futures market was relatively large even in the nascent stage, and it was not severely harmed despite the restrictive serial regulations and a consequent plunge in trading activities. The *IS* (*CFW*) in the futures market dropped from 37.54% (36.31%) in Period 1 to 35.27% (31.30%) in Period 2 and to 30.17% (25.65%) in Period 3. These findings do not change when we use the medians instead of the means.

These patterns are visually confirmed as well. Figure 4 plots the moving average of the daily *IS* and *CFW* in the spot, futures and options markets.[9] Even with short-term jiggles,

[8]Most recent studies attempt to estimate time-varying price discovery measures by employing a daily VECM. For more details, see Hasbrouck (2003), Chakravarty et al. (2004) and Chen and Chung (2012) among several others.

[9]The time series are smoothed with a trailing exponentially weighted moving average: $MA_t(a) = 0.2a_t +$

we observe a clear long-tern trend in each market. Specifically, the role of the spot market steadily diminishes over time, while the options market plays an increasingly important price discovery role. The contribution of the futures market is considerable and persistent, but gradually decreases.

Many previous papers examined the price discovery role in a bivariate setting. In other words, they estimate a bivariate VECM with a single derivative (either futures or options) market and its underlying spot market. To test this potential bias and confirm the importance of the trivariate analysis, we try estimating *IS*s and *CFW*s in the bivariate setting and report the results in Appendix B. When we consider only spot and futures markets, their estimated *IS*s are 32.58% and 67.42%, respectively, in the full sample. For the same analysis with spot and options data, the spot and options markets respectively take 32.24% and 67.76% of the *IS*. In other words, given that both futures and options markets exhibit superior price discovery ability to the underlying spot market, the contribution of the omitted derivative market is subsumed almost entirely by the included derivative market. This tendency is more pronounced recently when both derivatives are actively traded. As shown in Table 5, in Period 3, the sum of *IS*s in futures and options market is 84.6%, which is almost identical to 80.27% (85.1%), the *IS* in the futures (options) market obtained in the bivariate calculation. This finding reveals a possibility of potential bias in the previous literature in which only two markets, out of other actively traded markets, are analyzed.

4.2 Error-correction Coefficients

Since the *IS* and *CFW* from the three markets should sum to one by construction, they only capture the *relative* strength of price discovery. When the speed of information incorporation into the price concurrently increases or decreases in the three markets, these measures cannot effectively reflect this change. To comprehensively understand the changes in strength of price discovery, we consider whether and to what extent a market reacts to short-run

$0.8MA_{t-1}(a)$, where a is either *IS* or *CFW*.

deviation from a long-run equilibrium by examining the error-correction coefficient in the VECM equation. α in Equation (2) indicates how each market reacts at $t+1$ to changes in two cointegration error terms, $s_t - f_t$ and $s_t - o_t$. When the dependent variable is the spot return, we can easily expect the supposed signs of the coefficients; they should be negative for both cointegration error terms as long as the spot market actively corrects the errors. However, when the dependent variables are futures and option returns, the interpretation is not as straightforward. At a glance, it is difficult to expect how a futures return would react in response to an increase in log option basis $(s_t - o_t)$. For clear understanding, Equation (2) is re-written such that for each dependent variable, there are two cointegration error terms: log price deviations from the other two log prices. For example, when the futures return (Δf_{t+1}) is the dependent variable, the differences from log spot price $(f_t - s_t)$ and from log option price $(f_t - o_t)$ are the two cointegration error terms. Under this specification, the supposed signs of the error correction coefficients are always negative, and it suffices to test its magnitude and significance. Intuitively, if one market evolves regardless of the past cointegration error (short-term deviation from a long-run equilibrium) while other markets respond to it, it is likely that the market incorporates information earlier than others and plays a more important role in price discovery.

The VECM is estimated each day in a given sample period, and the means of the daily estimates and their corresponding Newey-West robust standard errors are presented in Table 6. Only error-correction coefficients are reported to save space. As expected, all coefficients are negative, but their magnitude and significance vary across the three markets and over time. In the overall sample, it turns out that the error correction occurs most strongly in the spot market. The extent to which the spot returns are explained by the cointegration errors and past returns is also the highest ($R^2 = 17.46\%$). These findings imply that the spot market tends to follow the other markets, rather than it leads other markets. In contrast, the derivatives markets correct the error to a lesser extent. Other things being equal, when a distance between the spot price and the futures (option) price widens, the magnitude of subsequent correction by the futures (option) price is less than a half of that by the spot price. The R^2 from the derivatives markets are relatively smaller, which means that the variations in the derivatives returns are attributed more to new information, compared to the spot return variation. The results indicate that the index derivatives markets in China have played its supposed price discovery role.

The subsample estimations indicate that the "absolute" strength of each market's price discovery exhibits dramatic changes over time; the response of the option (spot) market to the cointegration errors became weaker (stronger), and the variation in option (spot) returns attributed to new information has increased (decreased) in a monotone way. In Period 1, the options market was rather a follower than a leader. The deviations from a long-run equilibrium price were corrected mostly in the options market, and the R^2 for the option returns was almost 20%, which is quite high in a return time series regression. In contrast, the variation in futures and spot returns was mostly from new information (relatively low R^2s) and the futures and spot markets did not respond as much to the conintegration errors.

After the first structural break caused by restrictive regulations in August and September 2015, the magnitude of error-correction coefficients and the R^2 in the futures market more than doubled, implying that the price discovery role of the futures markets was severely weakened. This was not clearly shown in the *IS* and *CFW* analyses, possibly because the information processing ability in all three markets was concurrently affected due to common market shocks and the *IS* and *CFW* only reflect the *relative* price discovery. In Period 3, the options market substantially matures and plays a major role in price discovery. Option returns never respond to the past cointegration errors and its R^2 is as low as 4.95%, which means that the option price mostly reacts only to new information. The futures market does not respond as much to the deviation from the spot market, but it more strongly corrects the deviation from the options market than before. The tendency that spot market follows the derivatives markets is more pronounced in Period 3.

4.3 Volatility Spillover Effects

*IS*s and *CFW*s are calculated mainly from the error correction coefficients, which indicate how each market reacts to the deviation from the long-run common trend. To further evaluate the informativeness of each market, it is also important to examine how each market reacts to shocks in other markets. If shocks in one market affects the prices in other markets more than the other way around, then the market is said to play more important roles in price discovery. For this examination, we conduct the forecast error variance decomposition as suggested by Pesaran and Shin (1998) and Diebold and Yilmaz (2012).

Recall Equation (3), the VMA(∞) representation of the first difference in price vector time series:

$$\Delta p_t = \sum_{k=0}^{\infty} \Psi_k \epsilon_{t-k}. \tag{5}$$

Following Pesaran and Shin (1998), we compute the generalized impulse response, which does not require orthogonalization of the shocks and is invariant to the variable ordering. Specifically, the h-period ahead generalized impulse response with respect to a unit innovation in variable j is defined as $\phi_j(h) = E[\Delta p_{t+h}|\epsilon_{jt} = 1, \Theta_{t-1}] - E[\Delta p_{t+h}|\Theta_{t-1}]$, where Θ_{t-1} is the known history of the economy up to time $t-1$ and ϵ_{jt} is the j^{th} entry in ϵ_t. Pesaran and Shin (1998) show that it can be calculated as follows:

$$\phi_j(h) = \omega_{jj}^{-1/2} \Psi_h \Omega e_j, \quad h = 0, 1, 2, ..., \tag{6}$$

where ω_{jj} is the j^{th} diagonal entry in Ω and e_j is a column vector which takes one for the j^{th} entry and zero for others. The entry in row i in $\phi_j(h)$ indicates the consequence of the i^{th}-ordered state variable at time $t+h$ with respect to a unit innovation in j^{th}-ordered state variable in time t.

The idea of the generalized impulse response enables us to obtain the generalized forecast error variance decomposition, which is also invariant to the state variable ordering. Specifically, the generalized h-step ahead forecast error variance of the i^{th} variable attributed to the innovations in the j^{th} variable, denoted by $\theta_{ij}(h)$, is

$$\theta_{ij}(h) = \frac{\omega_{jj}^{-1} \sum_{k=0}^{h-1} (e_i' \Psi_k \Omega e_j)^2}{\sum_{k=0}^{h-1} e_i' \Psi_k \Omega \Psi_k' e_i}, \quad i, j = 1, 2, 3, \quad h = 0, 1, 2, ..., \tag{7}$$

For better economic interpretation, we normalize this measure so that the generalized forecast error variances of a variable accounted for by all variables sum to one: $\tilde{\theta}_{ij}(h) = \frac{\theta_{ij}(h)}{\sum_{j=1}^{3} \theta_{ij}(h)}$. Following Diebold and Yilmaz (2012), $\tilde{\theta}_{ij}(h)$ is interpreted as the gross volatility spillover transmitted from variable j to variable i. Similarly, the net volatility spillover from variable j to variable i is defined as $\tilde{\theta}_{ij}(h) - \tilde{\theta}_{ji}(h)$. We choose the one-hour horizon ($h = 60$) to capture the long-run spillovers. From these measures, we can learn the extent to which shocks in one market accounts for the variation of other markets.

Table 7 presents the gross spillover effects from one market to another, and the net spillover effects from a market. The (i, j) entry in the gross spillover represents the estimated contribution to the forecast error variance of market i coming from innovations of market j, while the entry in the net spillover is the difference between the spillover from market i to all other markets and the spillover from all other markets to market i. The spillovers are estimated for each day and the values in the table are the average of the daily estimates in a given sample period. The daily net spillover from each market is depicted in Figure 7.

In the overall sample, the volatility spillover from the spot market to the other markets is 40.73%, while that to the spot market from the others is 44.20%. That is, the spot market is more influenced by the innovations in the other markets than the other way around, which is reflected by the negative net spillover (-3.47%). In the whole sample, only the futures market exerts positive net spillover effects over the other markets. The subsample analysis shows the results consistent with previous subsections. In Period 1 when the options market was immature, its gross spillover to the other markets was only 39.93% whilst that to the options market was 49.24%. The spot and futures markets have the positive net spillover effects. Since then, however, the net spillover from the options market has steadily increased and finally reaches 4.52% in Period 3. The net spillover from the futures market has remained positive almost all the time, but slightly weakened over time. The volatility spillover analysis confirms the major price discovery role in the derivatives markets, particularly in the options market.

4.4 Determinants of Price Discovery

The analyses in previous sections show that the strength of the price discovery role in the derivatives markets fluctuates over time. To better understand the factors that drive this fluctuation, this subsection analyzes how price discovery abilities in the futures and options markets vary with market conditions. Specifically, we regress IS and CFW on the ratio of daily trading volume of futures and options to that of the spot (RTV_f and RTV_o), the open interest of futures and options (OI_f and OI_o), the ratio of daily return standard deviation of futures and options to that of the spot (RSD_f and RSD_o), and the absolute value of average log futures- and options-basis ($Abs.LogBasis_f$ and $Abs.LogBasis_o$). Chakravarty et al. (2004) and Chen and Chung (2012) find that the trading volume and market volatility are the determinant of the price discovery in a market. We include the open interest to further reflect the trading activities. The absolute value of the log basis is the gap between the two prices and represents the arbitrage opportunities among the markets.

Table 8 tabulates the estimation results. The results show that the information share and common factor weights in the options market are higher when its open interest is larger and the relative volatility is smaller. When the competitor (futures) has more arbitrage opportunities, the price discovery ability in the options market decreases. These findings are generally consistent with the aforementioned literature.

In the futures market, the price discovery becomes stronger with smaller return volatility and more arbitrage opportunities, which is in line with options market. Interestingly, the futures trading activities do not significantly co-vary with the futures price discovery. When a series of stringent regulations, including an abrupt increase in transaction costs, were imposed in the futures market and the trading volume subsequently plunged 90% in August and September 2015, the futures market still made considerable contributions to price discovery. Its IS and CFW did not significantly decrease after these regulations. This finding is evidence against the trading cost hypothesis. If this hypothesis held, we could have observed a significant drop in IS and CFW in the futures market after the sudden and almost exogenous increase in the transaction costs.

Both the SSE50 Index futures and the SSE50 ETF options were launched in early 2015, but the futures market started exhibiting a strong price discovery from the beginning while the options market did not. What makes a difference in the price discovery ability? We conjecture that investors' trading experience crucially matters in a nascent market. When the SSE50 Index futures was launched, the futures investors had already accumulated five-year of trading experiences since the introduction of the first index futures (CSI300 Index futures) in 2010. In contrast, the SSE50 ETF options were the very first exchange-traded options and options investors had no such experience. They needed time to familiarize themselves with the new financial instrument. This explanation is consistent with the fact that when the CSI300 Index futures began trading in 2010, the spot market played a more important role in price discovery than the futures market (Yang et al., 2012; Sohn and Zhang, 2017). This result implies that in a nascent market, the price discovery ability of a derivative market does not necessarily depends solely on its transaction cost but on whether investors in the market are mature and experienced sufficiently.

5 Conclusion

We study the time-varying price discovery roles in the spot, futures and options markets using the SSE50 Index-based securities in China. The recent and almost concurrent launches of the SSE50 ETF options and SSE50 Index futures (February and April 2015, respectively) provide a good setting for evaluating the development course of the two derivatives markets.

We find that the derivatives markets started to play their supposed price discovery role after several months since their launches. The leading price discovery role of the spot market quickly declined after the launch of the two derivatives. The contributions of the futures market have been considerably large since their launch, while those of the options market was mediocre in the beginning but recently becomes dominant. The spillover analyses confirm the findings from information shares and common factor weights. Trading activities, volatility and arbitrage opportunities are the determinants of options price discovery, which supports the trading cost hypothesis. In the futures market, however, changes in transaction costs and consequent variation in trading activities cannot explain the fluctuation in futures price discovery, which is evidence against the hypothesis. We provide a potential explanation that investors' experience could be crucial in a nascent market such as China.

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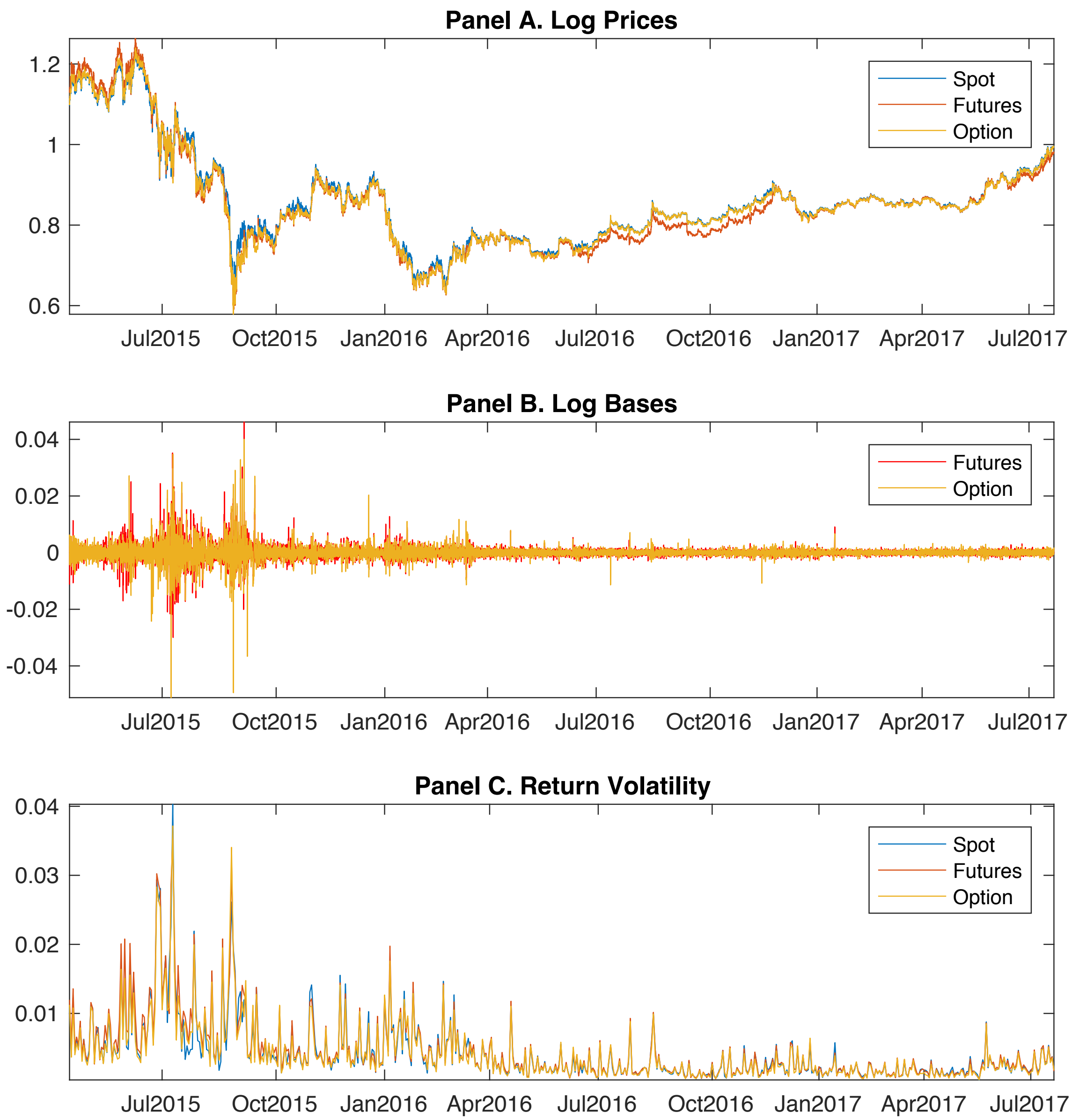
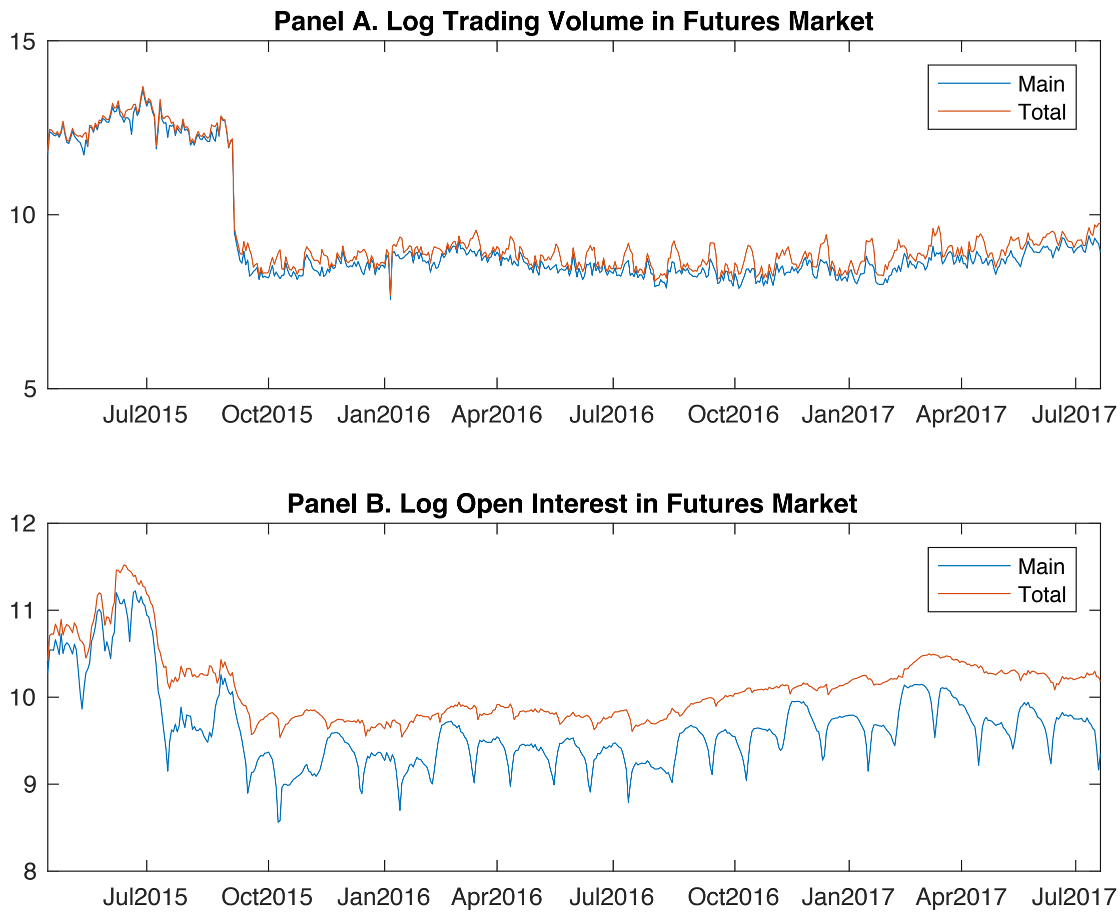
Figure 1: Log Prices in the Spot, Futures, and Options markets



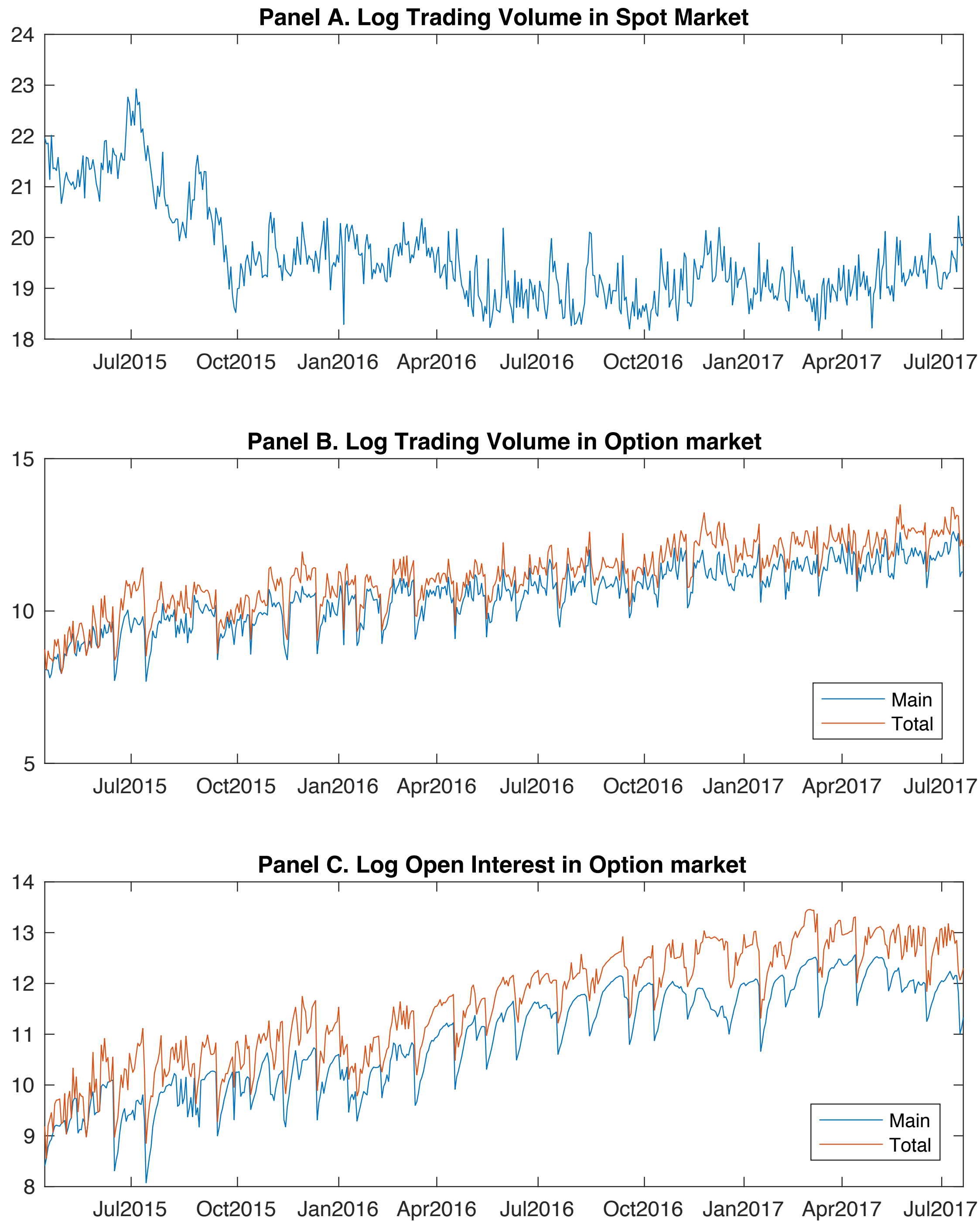
Note: Figure 1 plots the time series of log prices of SSE50 ETF (spot), SSE50 ISSE50ndex futures and SSE50 ETF option at the 1-minute frequency from April 16, 2015 to July 20, 2017. The log basis is defined as the difference between the spot log price and the corresponding derivative log price, demeaned each day. Return volatility is calculated each day by the standard deviation of 1-minute returns.

Figure 2: SSE50 Index Futures Trading Activities



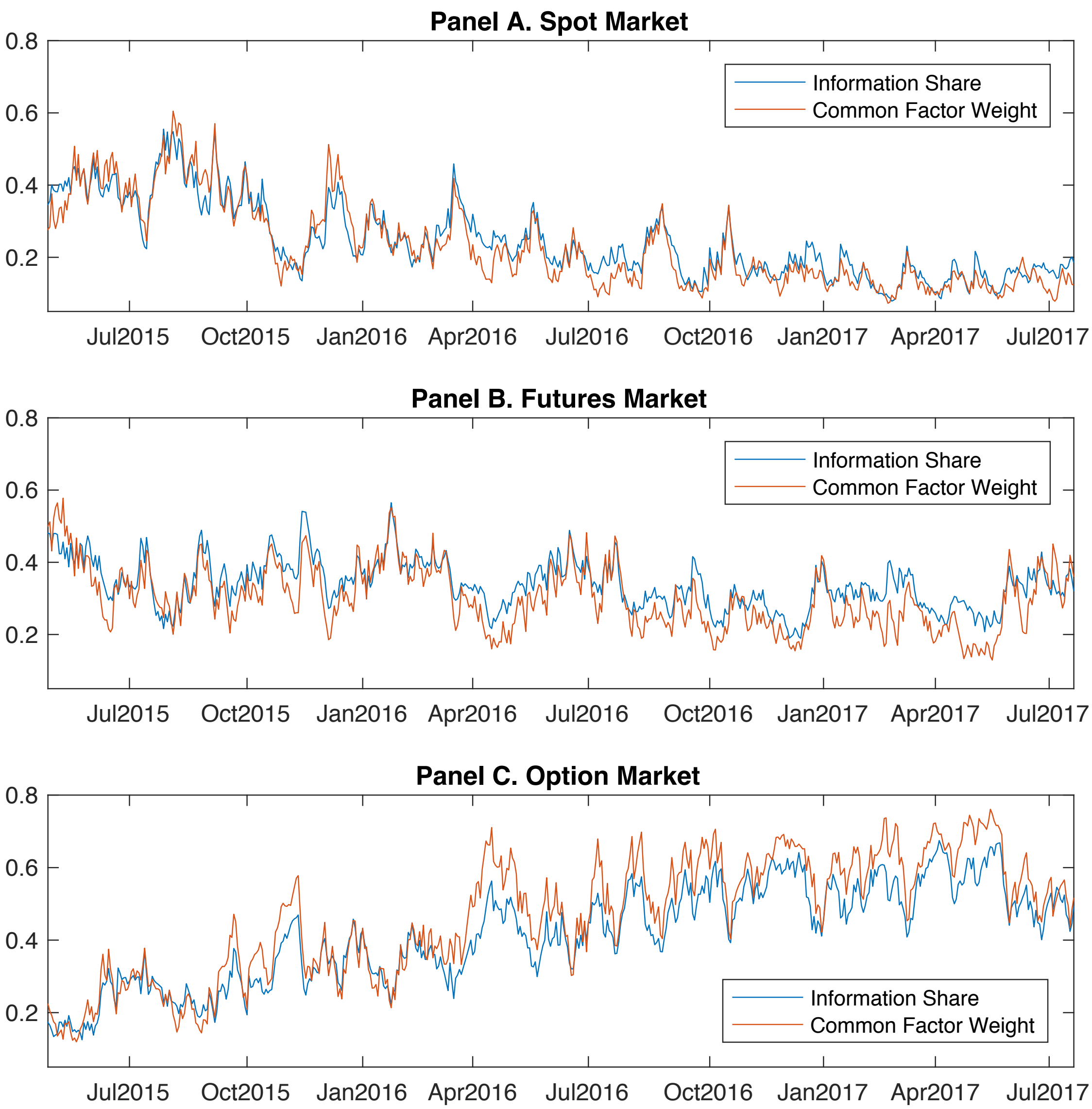
Note: Figure 2 plots the daily log trading volume and log open interest of the SSE50 Index futures contracts. There are four simultaneously traded contracts with different expiration dates. The main contract is the one with the largest trading volume (open interest).

Figure 3: SSE50 ETF and Its Options Trading Activities



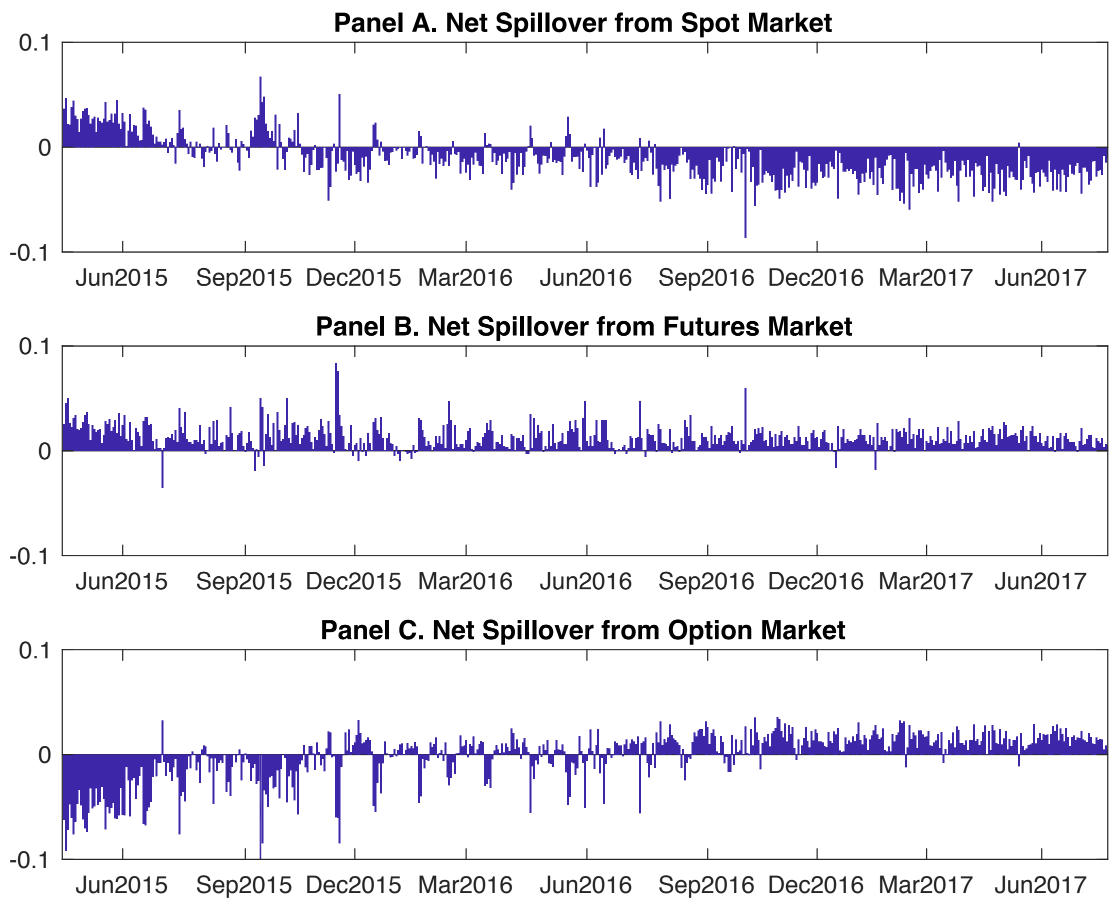
Note: Figure 3 plots the daily log trading volume of the SSE50 ETF, and the daily log trading volume and log open interest of its at-the-money option contracts. There can be multiple at-the-money call and put options within a day. The main contract is the one with the largest put and call combined trading volume (open interest).

Figure 4: Information Shares and Common Factor Weights



Note: Figure 4 plots the daily information shares and common factor weights in the spot, futures and options markets. Information shares and common factor weights are calculated from a vector error correction model of prices in the three markets according to Hasbrouck (1995) and Gonzalo and Granger (1995), respectively. The lag length of the model is chosen by the Bayesian information criterion. The time series are smoothed with a trailing exponentially weighted moving average: $MA_t(a) = 0.2a_t + 0.8MA_{t-1}(a)$, where a is either information share or common factor weight.

Figure 5: Net Spillover from Each Market



Note: Figure 5 depicts the daily long-horizon (60-minute) net spillovers. Following Diebold and Yilmaz (2012), the net spillover from market i is defined as the gross spillover from market i to all other markets minus that to market i from all other markets.

Table 1: Timeline of Major Regulation Changes

Announcement	Effective date	Market	Contents
Feb 3, 2015	Feb 9, 2015	Options	Introduction of SSE50 ETF options
Mar 27, 2015	Apr 16, 2015	Futures	Introduction of SSE50 Index futures
Mar 30, 2015	Apr 16, 2015	Futures	Transaction fee: 0.0025% & Filing fee: 0.01% of intraday closing transaction amount; Margin requirement: 10% of contract value
Mar 30, 2015	Apr 1, 2015	Options	Position limit increase
May 3, 2015	May 4, 2015	Options	Position limit decrease
Jun 3, 2015	Jun 3, 2015	Options	Temporary exemption of transaction fees
Jul 1, 2015	Jul 1, 2015	Options	handing fee: 0.02% of amount
Jul 31, 2015	Aug 3, 2015	Futures	Transaction fee: 0.0023% of amount & Filing fee: CNY1 per transaction
Aug 25, 2015	Aug 26, 2015	Futures	Transaction fee: 0.0115% of amount & Filing fee: CNY1 per transaction
	Aug 26, 2015	Futures	Margin requirement: 12% of contract value for non-hedging position
	Aug 27, 2015	Futures	Margin requirement: 15% of contract value for non-hedging position
	Aug 28, 2015	Futures	Margin requirement: 20% of contract value for non-hedging position
Aug 28, 2015	Aug 31, 2015	Futures	Margin requirement: 30% of contract value for non-hedging position
Sep 2, 2015	Sep 7, 2015	Futures	Transaction fee: 0.23% of amount & Filing fee: CNY1 per transaction
		Futures	Margin requirement: 40% (20%) of contract value for non-hedging (hedging) position
		Futures	Maximum limit on daily non-hedging trading: 10 contracts[a]
Sep 7, 2015	Sep 8, 2015	Options	position limit decrease
Oct 28, 2016	Nov 1, 2016	Options	handling fee: 0.013% of amount
Feb 16, 2017	Feb 17, 2017	Futures	Maximum limit on daily non-hedging trading: 20 contracts
		Futures	Margin requirement: 20% of contract value for non-hedging position
		Futures	Transaction fee: 0.092% of amount & Filing fee: CNY1 per transaction

Note: Table 1 shows the timeline of major regulation changes in the derivatives markets in China.

[a]If the non-hedging open trades within a day is greater than 10 contracts in a single product, it is considered as "abnormal trading" and scrutinized.

Table 2: Structural Breaks: Recursive Chow Tests

Structural Break Point	Variables	Remarks
September 7, 2015	TV_s**, OI_f**, SD_s***, SD_f***, SD_o***, SD_{sf}***, SD_{so}***	Futures margin requirement increased from 30% to 40% of contract value (for non-hedging purpose); from 10% to 20% (for hedging purpose); Futures commission fees increased from 0.0115% to 0.23% of the closed transaction value; Announced on September 2; Implemented on September 7, 2015
November 1, 2016	TV_s**, TV_f**, TV_o**, OI_f*, SD_s**, SD_f**, SD_o*, SD_{so}***	Option commission fees reduced from 0.02% to 0.013% of the closed transaction value; Announced on October 28; Implemented on November 11, 2016

Note: Table 2 shows the result of recursive Chow tests. We consider ten variables for testing structural breaks: daily trading volume of three markets (TV_s, TV_f, TV_o), daily open interests of two derivative markets (OI_f, OI_o), daily return volatility of three markets (SD_s, SD_f, SD_o) and daily volatility of two bases (SD_{sf}, SD_{so}). Each variable is assumed to follow an autoregressive process. A Chow test is conducted for each variable using the 60-trading-day moving window. The null hypothesis is no structural break, while the alternative hypothesis is a break at the 31st observation. For each estimation window, we choose the optimal lag length by the Bayesian information criterion. A structural break occurs if the null is rejected for more than two-third of ten variables. We record only one structural break within 60 trading days. If multiple breaks are detected within 60 trading days, the day with the most rejections of the null is recorded as a single break. *** (**, *) indicates the 1% (5%, 10%) significance level.

Table 3: Descriptive Statistics

	Overall Apr17, 2015 - Jul20, 2017	*Period 1* Apr17, 2015 - Sep02, 2015	*Period 2* Sep07, 2015 - Oct31,2016	*Period 3* Nov01, 2016 - Jul20, 2017
	Panel A. Intraday 1-min Returns			
Spot (%)	-0.00007	-0.00126	0.00005	0.00038
	(0.11701)	(0.22426)	(0.08883)	(0.05025)
Futures (%)	-0.00011	-0.00183	0.00016	0.00041
	(0.12458)	(0.23720)	(0.09751)	(0.04892)
Option (%)	-0.00008	-0.00168	0.00019	0.00038
	(0.11193)	(0.21346)	(0.08678)	(0.04560)
Obs.	132,638	23,519	66,639	42,480
	Panel B. Daily Trading Activities			
Trading Volume				
Spot (in thousands)	596,752	2,144,850	283,652	233,145
	(989,559)	(1,593,240)	(166,777)	(104,833)
Futures	55,543	288,657	5,118	5,956
	(119,770)	(122,733)	(1,537)	(1,996)
Futures Total	63,234	323,583	6,632	8,307
	(133,408)	(135,037)	(2,122)	(3,059)
Option	56,600	11,817	37,956	110,783
	(50,821)	(7,207)	(22,853)	(51,394)
Option Total	113,154	24,222	68,336	233,038
	(110,237)	(18,145)	(43,366)	(113,970)
Open Interest				
Futures	17,684	35,061	11,693	17,507
	(11,746)	(18,335)	(2,454)	(3,695)
Futures Total	27,013	49,126	18,343	28,436
	(14,789)	(22,301)	(2,244)	(3,416)
Option	86,242	14,421	61,886	164,398
	(72,347)	(6,210)	(44,581)	(57,703)
Option Total	177,385	27,100	112,934	362,185
	(158,868)	(14,234)	(78,602)	(126,198)
Obs.	554	98	279	177

Note: Table 3 reports the descriptive statistics of the intraday 1-minute returns (Panel A) and the daily trading activities (Panel B) of three securities based on the SSE50 Index. Spot indicates the SSE50 Index-tracking ETF managed by China Asset Management Co., Ltd. Futures (Option) indicates the SSE50 Index futures (SSE50 ETF at-the-money option) contract with the largest trading volume. The option return is obtained from the price of the SSE50 ETF implied by the put-call parity. Futures Total considers the sum of the four futures contracts with different expiration dates. Option Total considers the sum of all at-the-money options. The values in parenthesis are the corresponding standard deviations.

Table 4: Cointegration Tests

	Overall	*Period 1*	*Period 2*	*Period 3*
	Percentage of rejecting H_0			
Engle-Granger (H_0 : No cointegration)	93.14%	69.39%	97.13%	100.00%
Johansen (H_0 : Cointegration rank of 2)	19.13%	14.29%	20.79%	19.21%
	Percentage of cointegrated trading days			
Judged by both tests	74.55%	57.14%	76.70%	80.79%
Judged by either test	99.46%	97.96%	99.64%	100.00%
Obs.	554	98	279	177

Note: Table 4 presents the summary results of the daily cointegration tests. The Engle-Granger test assesses the null hypothesis of no cointegration among the log (implied) prices of SSE50 ETF, SSE50 Futures and SSE50 ETF option. The Johansen test assesses the null hypothesis of cointegration rank equal to 2 against the alternative of 3. The number of lags in the tests is set to zero and the significance level is 1%.

Table 5: Information Shares and Common Factor Weights

	Information shares			Common factor weights		
	Spot	Futures	Option	Spot	Futures	Option
Overall						
Mean	24.48%	34.03%	41.49%	23.14%	30.36%	46.50%
Median	19.14%	31.62%	41.71%	17.97%	25.50%	50.50%
SD	17.09%	15.36%	19.86%	19.51%	20.80%	25.08%
Period 1						
Mean	40.16%	37.54%	22.30%	40.95%	36.31%	22.75%
Median	39.79%	35.01%	21.41%	39.54%	32.51%	19.98%
SD	17.50%	18.11%	13.60%	22.79%	23.46%	15.67%
Period 2						
Mean	24.85%	35.27%	39.87%	23.19%	31.30%	45.51%
Median	20.93%	34.02%	38.70%	18.50%	27.61%	47.26%
SD	16.46%	15.50%	17.96%	18.66%	20.96%	24.72%
Period 3						
Mean	15.40%	30.17%	54.43%	13.41%	25.65%	60.94%
Median	13.03%	28.23%	57.79%	10.61%	23.32%	65.02%
SD	10.19%	12.57%	15.84%	9.65%	17.89%	18.76%

Note: Table 5 reports the information shares and the common factor weights of the spot, futures and options markets. They are calculated from a vector error correction model of prices in the three markets according to Hasbrouck (1995) and Gonzalo and Granger (1995) at one-minute frequency. The model is estimated for each day in a given sample period. The lag length of the model is chosen by the Bayesian information criterion. The values in the table are summary statistics for these daily estimates.

Table 6: Error Correction Coefficients in VECM

Dependent variable	Error correction term			R^2
	Log price deviation from			
	Spot	Futures	Option	
Overall				
Spot return (Δp_s)		-0.121***	-0.098***	17.46%
		(0.007)	(0.010)	
Futures return (Δp_f)	-0.055***		-0.102***	6.92%
	(0.004)		(0.006)	
Option return (Δp_o)	-0.029***	-0.061***		11.41%
	(0.007)	(0.008)		
Period 1				
Spot return (Δp_s)		-0.053***	-0.039***	8.58%
		(0.015)	(0.012)	
Futures return (Δp_f)	-0.033***		-0.041***	3.56%
	(0.010)		(0.009)	
Option return (Δp_o)	-0.114***	-0.065***		19.54%
	(0.023)	(0.016)		
Period 2				
Spot return (Δp_s)		-0.126***	-0.099***	18.06%
		(0.009)	(0.015)	
Futures return (Δp_f)	-0.070***		-0.107***	7.80%
	(0.006)		(0.008)	
Option return (Δp_o)	-0.016***	-0.099***		12.71%
	(0.006)	(0.010)		
Period 3				
Spot return (Δp_s)		-0.149***	-0.128***	21.33%
		(0.011)	(0.015)	
Futures return (Δp_f)	-0.042***		-0.130***	7.36%
	(0.007)		(0.010)	
Option return (Δp_o)	-0.002	-0.002		4.95%
	(0.005)	(0.009)		

Note: Table 6 tabulates the estimated coefficients of the error correction terms obtained from a vector error correction model of prices in the three markets at one-minute frequency. The model is estimated for each day in a given sample period. The lag length of the model is chosen by the Bayesian information criterion. The table reports means of the daily estimates and their corresponding Newey-West robust standard errors. For each dependent variable, there are two error correction terms: log price deviation from the other two log prices. For example, when the spot return (Δp_s) is the dependent variable, the differences from log futures price ($p_s - p_f$) and from log option price ($p_s - p_o$) are the two error correction terms. The coefficients for other terms (constant and autoregressive terms) are not reported to save space, but available upon request. *** (**, *) indicates the 1% (5%, 10%) significance level.

Table 7: Spillover Table

	To	From			
		Spot	Futures	Option	The Others
Overall					
Gross Spillover	Spot	55.80%	22.11%	22.08%	44.20%
	Futures	19.67%	52.66%	27.67%	47.34%
	Option	21.06%	29.11%	49.83%	50.17%
	The Others	40.73%	51.23%	49.76%	
Net Spillover		-3.47%	3.89%	-0.41%	
Period 1					
Gross Spillover	Spot	48.14%	31.42%	20.44%	51.86%
	Futures	31.14%	49.37%	19.49%	50.63%
	Option	24.83%	24.41%	50.76%	49.24%
	The Others	55.97%	55.83%	39.93%	
Net Spillover		4.11%	5.20%	-9.31%	
Period 2					
Gross Spillover	Spot	57.60%	20.20%	22.20%	42.40%
	Futures	17.92%	55.25%	26.83%	44.75%
	Option	21.22%	28.29%	50.48%	49.52%
	The Others	39.15%	48.49%	49.04%	
Net Spillover		-3.25%	3.73%	-0.48%	
Period 3					
Gross Spillover	Spot	57.13%	20.08%	22.79%	42.87%
	Futures	16.19%	50.38%	33.43%	49.62%
	Option	18.75%	32.96%	48.30%	51.70%
	The Others	34.94%	53.04%	56.22%	
Net Spillover		-7.93%	3.41%	4.52%	

Note: Table 7 shows the long-horizon (60-minute) gross and net spillovers. The (i, j) entry in the gross spillover represents the estimated contribution to the forecast error variance of market i coming from innovations of market j, while the entry in the net spillover is the difference between the spillover from market i to all other markets and the spillover from all other markets to market i. The spillovers are estimated for each day and the values in the table are the average of the daily estimates in a given sample period.

Table 8: Time Variation in Information Shares and Common Factor Weights in Derivatives Markets

	Futures market		Options market	
	IS	CFW	IS	CFW
RTV_f	-0.230	-0.140	-0.133	-0.314**
	(0.162)	(0.198)	(0.112)	(0.134)
RTV_o	-0.0378	-0.0205	0.0747	0.0703
	(0.0469)	(0.0730)	(0.0562)	(0.0745)
OI_f	0.000579	0.000330	-0.000782	-0.00107
	(0.000660)	(0.000930)	(0.000760)	(0.000802)
OI_o	-0.000353**	-0.000519**	0.000886***	0.00103***
	(0.000179)	(0.000244)	(0.000209)	(0.000257)
RSD_f	-0.117*	-0.130*	0.0255	0.0502
	(0.0613)	(0.0693)	(0.0518)	(0.0618)
RSD_o	0.134**	0.183***	-0.204***	-0.274***
	(0.0589)	(0.0682)	(0.0567)	(0.0661)
$Abs.LogBasis_f$	2.702*	3.787*	-5.340***	-5.507***
	(1.479)	(1.985)	(1.495)	(1.641)
$Abs.LogBasis_o$	-2.348	-3.655*	1.484	0.599
	(1.480)	(1.875)	(1.508)	(1.603)
$Constant$	0.369***	0.308***	0.543***	0.644***
	(0.0536)	(0.0601)	(0.0555)	(0.0637)
Obs.	551	551	551	551
R^2	0.078	0.073	0.404	0.362
adjusted-R^2	0.064	0.059	0.395	0.353

Note: Table 8 tabulates the regression results of the daily information share (common factor weights) in the futures and options markets on several market variables. $RTV_f(RTV_o)$ is the ratio of the daily trading volume in the futures (options) market to that in the spot market. $OI_f(OI_o)$ is the ratio of the daily open interest in the futures (options) market to that in the spot market. $RSD_f(RSD_o)$ is the ratio of the daily return standard deviation in the futures (options) market to that in the spot market. $Abs.LogBasis_f(Abs.LogBasis_o)$ is the absolute value of the average log futures (options) basis. The values in parenthesis are the corresponding robust standard errors. *** (**, *) indicates the 1% (5%, 10%) significance level.

Appendix A

This appendix section describes the details of the SSE50 Index futures contract and the SSE50 ETF option contract.

Table A1: Details of SSE50 Index Futures Contract

Item	Details
Underlying	SSE 50 Index
Tick size	Quotations for the contact is integer multiples of 0.2 index points
Contract multiplier	The value of the contract equals the futures index points multiplying CNY300.
Contract month	Current month, next month, and subsequent two quarter-ending months
Expiration date	Third Friday of the contract month
Trading hours	9:30-11:30 and 13:00-15:00[1]
Trading mechanism	T+0 trading system
Settlement method	Cash settlement
Exchange	China Financial Futures Exchange

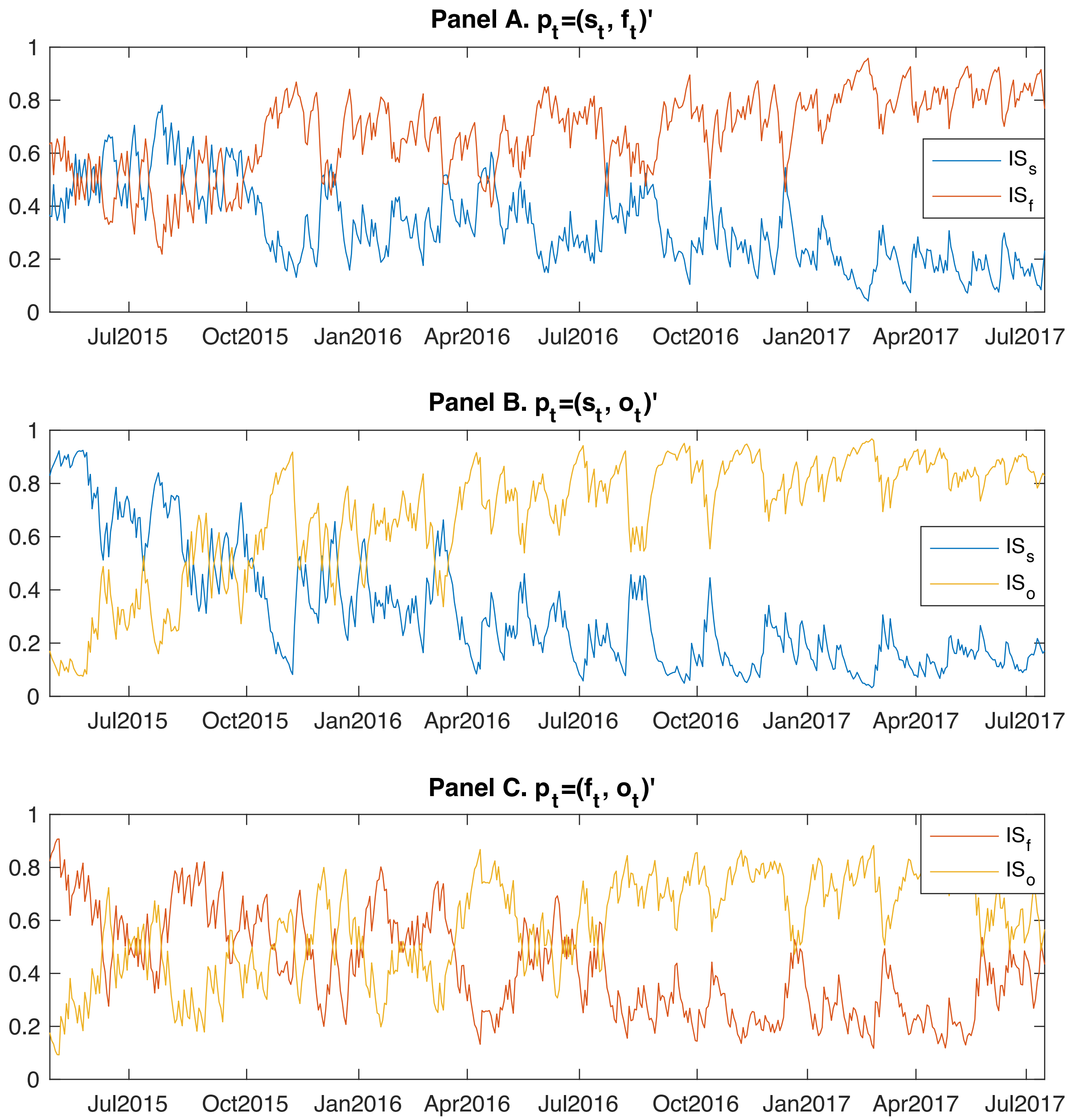
Table A2: Details of SSE50 ETF Option Contract

Item	Details
Underlying	SSE50 ETF
Contract type	Call option and put option
Exercise style	European option
Contract unit	Each contract corresponds to 10,000 SSE50 ETF shares.
Contract month	Current month, next month, and subsequent two quarter-ending months
Expiration date	Fourth Wednesday of the contract month
Strike price	Five strike prices (one at-the-money, two out-of-the-money, and two in-the-money) are set for the first listings. Options with new strike prices are added when the change in spot price results in fewer than two out-of-the-money options or two in-the-money options.
Trading hours	9:30-11:30 and 13:00-15:00
Trading mechanism	T+0 trading system
Settlement method	Physical delivery
Exchange	Shanghai Stock Exchange

Appendix B

In this appendix section, we present the bivariate analysis results in which we consider only two out of the three price time series: SSE50 ETF, SSE50 Index Futures and SSE50 ETF Options.

Figure B1: Information Shares from Bivariate VECM Estimation



Note: Figure B1 plots the daily information shares of the spot, futures and options markets, when they are estimated from bivariate VECMs. For example, Panel A is obtained from a VECM only with spot and futures prices. The lag length of the model is chosen by the Bayesian information criterion. The time series are smoothed with a trailing exponentially weighted moving average: $MA_t(IS) = 0.2IS_t + 0.8MA_{t-1}(a)$, where IS is the information share.

Table B1: Information Shares from Bivariate VECMs

		$p_t = (s_t, f_t)'$		$p_t = (s_t, o_t)'$		$p_t = (f_t, o_t)'$	
		IS_s	IS_f	IS_s	IS_o	IS_f	IS_o
Full	Mean	32.58%	67.42%	32.24%	67.76%	42.33%	57.67%
	Median	22.12%	77.88%	15.21%	84.79%	34.11%	65.89%
	SD	31.04%	31.04%	34.48%	34.48%	34.28%	34.28%
Period 1	Mean	51.88%	48.12%	69.71%	30.29%	64.13%	35.87%
	Median	59.47%	40.53%	84.25%	15.75%	80.41%	19.59%
	SD	35.19%	35.19%	32.76%	32.76%	36.81%	36.81%
Period 2	Mean	34.11%	65.89%	30.34%	69.66%	43.67%	56.33%
	Median	25.68%	74.32%	14.49%	85.51%	39.30%	60.70%
	SD	29.71%	29.71%	32.79%	32.79%	33.53%	33.53%
Period 3	Mean	19.73%	80.27%	14.90%	85.10%	28.41%	71.59%
	Median	10.48%	89.52%	9.46%	90.54%	21.78%	78.22%
	SD	24.09%	24.09%	19.20%	19.20%	26.72%	26.72%

Note: Table B1 reports the information shares of the spot, futures and options markets, when they are estimated from bivariate VECMs. For example, the first two columns are obtained from a VECM only with spot and futures prices. The model is estimated for each day in a given sample period. The lag length of the model is chosen by the Bayesian information criterion. The values in the table are summary statistics for these daily estimates.