INTRADAY PRICE DISCOVERY AND VOLATILITY TRANSMISSION IN STOCK INDEX AND STOCK INDEX FUTURES MARKETS: EVIDENCE FROM CHINA

JIAN YANG*
ZIHUI YANG
YINGGANG ZHOU

Using high-frequency data, this study investigates intraday price discovery and volatility transmission between the Chinese stock index and the newly established stock index futures markets in China. Although the Chinese stock index started a

We thank Warren Bailey, Hui Chen, Hung-gay Fung, Bob Webb (the editor), an anonymous referee, and conference/seminar participants at the Seventh Chinese Finance Association Annual Meetings, Nankai University, Southern Fund Management Co. Ltd for helpful comments on earlier versions. Z. Yang gratefully acknowledges financial support from the Humanities and Social Sciences grant of the Chinese Ministry of Education (08JC790104), Guangdong Universities Humanities and Social Sciences Yumiao Fund (WYM08024), the Foundation for the Authors of Excellent Doctoral Dissertation of Guangdong Province (sybzzxm201003), the Fundamental Research Funds for the Central Universities, and the research grant from the Economic Research Center at Sun Yat-Sen University.

*Correspondence author, The Business School, PO Box 173364, University of Colorado Denver, Denver, Colorado 80217-3364. Tel: (303) 315-8423, Fax: (303) 315-8084, e-mail: Jian.Yang@ucdenver.edu

Received October 2010; Accepted December 2010

- *Jian Yang is an Associate Professor of Finance in the Business School at the University of Colorado Denver, Denver, Colorado.*
- *Zihui Yang is an Associate Professor of Finance in Lingnan College at the Sun Yat-Sen University, Guangzhou, People's Republic of China.*
- *Yinggang Zhou is an Assistant Professor of Finance and Real Estate in the Faculty of Business Administration at the Chinese University of Hong Kong, Hong Kong.*

The Journal of Futures Markets, Vol. 32, No. 2, 99–121 (2012)

Published online March 1, 2011 in Wiley Online Library (wileyonlinelibrary.com)
DOI: 10.1002/fut.20514

sharp decline immediately after the stock index futures were introduced, the cash market is found to play a more dominant role in the price discovery process. The new stock index futures market does not function well in its price discovery performance at its infancy stage, apparently due to high barriers to entry into this emerging futures market. Based on a newly proposed theoretically consistent asymmetric GARCH model, the results uncover strong bidirectional dependence in the intraday volatility of both markets. Jrl Fut Mark 32:99–121, 2012

1. INTRODUCTION

Price discovery performance of futures markets is an important issue that has received a lot of attention in the literature. Price discovery in futures markets is commonly defined as the use of futures prices to determine expectations of (future) cash market prices, and the price discovery performance of futures markets is crucial to the use of these markets. As asset prices appear to exhibit non-stationarity, a number of studies investigate the price discovery role of futures markets in a cointegration or related error correction model framework. See, for example, Ghosh (1993), Brenner and Kroner (1995), Yang, Bessler, and Leatham (2001), Chatrath, Christie-David, Dhanda, and Koch (2002), among others.

Another important issue is volatility transmission between futures markets and underlying cash markets. As pointed out in Chan, Chan, and Karolyi (1991, p. 659), ignoring the fact that return volatilities in the cash and futures markets vary in a related way can lead to incorrect inferences about the relation between the markets, and investigating the relationship between return volatility in the cash and futures markets can help us to learn more about how information flows between these two markets. Furthermore, the strength of volatility transmission may shed light on the risk-minimization hedging effectiveness of futures markets, another major function of futures markets (Lien & Yang, 2006, 2008).

Using high-frequency data, this study investigates price discovery and volatility transmission between the Chinese stock index and stock index futures markets. It contributes to the literature in the following aspects. First, to the best of our knowledge, this is the first study to explore price and volatility dynamics between the stock index and stock index futures markets in China. Although Chinese commodity futures markets have been much explored in the literature (e.g. Chan, Fung, & Leung, 2004; Fung, Liu, & Tse, 2010; Lee, Fung, & Liao, 2009), the stock index futures market was only recently introduced in April 2010. The existing literature on price discovery and/or volatility transmission between stock index and futures has primarily focused on developed markets (e.g. Abhyankar, 1995; Chan, 1992; Chan et al., 1991; Fleming, Ostdiek, & Whaley, 1996; Ghosh, 1993; Hodgson, Masih, & Masih, 2003; Stoll & Whaley, 1990), and emerging futures markets have not received much attention in the literature. One notable exception is Zhong, Darrat, and Otero (2004), who investigates the stock index futures market in Mexico. Indeed, most previous studies on developed markets suggest that the futures market generally leads the cash market and serves as a primary market of price discovery, while it is unclear whether such a conclusion can also be generally applied to the new futures markets in emerging economies. Thus, this study attempts to enrich the existing literature by investigating the case of China, the largest emerging economy in the world, which has a very unique market structure including the dominance of individual investors over institutional investors on the stock market (e.g. Ng & Wu, 2007).

Second, we test whether at any point of time the stock index futures has played a primary role in price discovery and thus led a sharp drop in cash market prices during the sample period (−27.3% in less than 3 months) using the recursive cointegration technique.[1] The recursive cointegration technique of Hansen and Johansen (1999) is applied to examine possible time-varying price discovery performance, which may be particularly revealing for nascent index futures markets. This relatively new technique, which has not yet been much employed in the futures market literature, can reveal the stability of the cointegration relationship and related adjustment coefficients (or lack of it), and help us to learn more about the length of time a new futures market would take to perform well in its price discovery function.[2] By contrast, the stability of the cointegration relationship and parameter constancy of associated error correction models are often assumed in earlier studies reviewed in Brenner and Kroner (1995) and Yang et al. (2001). Although immediately after the stock index futures were introduced, the underlying cash market prices started falling and experienced a drastic drop of 27.3% in less than 3 months, we find that the cash market plays a more dominant role in the price discovery process. The new stock index futures market does not function well in its price discovery performance at its infancy stage, apparently due to high barriers to entry into this emerging futures market.

[1]Since the seminal work of Miller (1977), there is also a large body of the literature exploring the impact of short sale restrictions on asset prices. As investors did not have the ability to short stocks in China, investors can now implement short sales due to the opening of the futures market. Thus, the introduction of the stock index futures contract might be responsible for the sharp decline in the stock index after the launch of the futures market. The issue deserves further investigation.

[2]Owing to various reasons (e.g. illiquidity), the price discovery function of a futures market might not be established, and the spot market might tend to lead the futures market during a sample period. Nevertheless, it is totally an empirical question to determine whether a futures market might perform the price discovery function.

Third, to simultaneously allow for volatility spillover between cash and futures markets and asymmetric basis effects on returns, volatilities and covariances, built on the recent work of Kogan, Livdan, and Yaron (2009), a theoretically consistent bivariate asymmetric error correction model (ECM)–GARCH with the BEKK specification is proposed in this study. Kogan et al. (2009) show a V-shape relationship between the volatility of futures prices and the basis, i.e. the effect of the basis on futures price volatility is positive (negative) when the basis is positive (negative).[3] Lien and Yang (2006, 2008) also allow for the asymmetric effects of positive and negative bases, and confirm the non-monotonic effect of basis pointed out in Kogan et al. (2009). Compared with the Dynamic Conditional Correlation (DCC) specification used in Lien and Yang (2006, 2008), the bivariate GARCH model in this study better accounts for the volatility spillover between cash and futures markets, as the volatility only depends on its own history in the DCC specification. Furthermore, the model specification not only guarantees positive definiteness after allowance for asymmetric effects of the basis, which is still not well addressed in previous studies, but also extends the GARCH-X model specification used in the literature, which is somewhat ad hoc and does not allow for the asymmetric basis effect (e.g. Bhar, 2001; Lee, 1994; Ng & Pirrong, 1994). We also extend asymmetric covariance GARCH model specification of Kroner and Ng (1998) by allowing for asymmetric covariance to be affected by any separate economic variables (e.g. the basis) rather than negative (or positive) return shocks.

The remainder of the study is organized as follows. Section 2 describes the data we use for this study. Section 3 briefly describes the empirical methodology, and section 4 reports and discusses empirical findings. Finally, the conclusions are summarized in Section 5.

2. DATA DESCRIPTIONS

The Chinese stock market has grown rapidly and received increasing attention since their inception in the early 1990s. China's two stock exchanges, the Shanghai Securities Exchange and the Shenzhen Securities Exchange, were established in 1990 and 1991, respectively. However, for a long time, there was no broadly based stock index reflecting the performance across both stock exchanges. As the first index designed to measure overall performance of China A shares available to domestic investors only, the CSI 300 Index was created on April 8, 2005.[4] The index, complied and published by the China Securities

[3]Note that while the basis can be defined as either the futures price minus the cash price or the reverse, the definition in this study is the futures price minus the cash price, and consistent with Kogan et al. (2009) and Chatrath et al. (2002) but opposite to Lien and Yang (2006, 2008).
[4]The reader is referred to Bailey (1994) for the more detailed discussion about the Chinese stock market and A and B shares available to domestic and foreign investors, respectively.

Index Company Ltd, consists of 300 large-capitalization and actively traded stocks listed on the Shanghai or Shenzhen Stock Exchanges, and represents about 70% of the total market capitalization of both stock exchanges. Therefore, it is widely perceived to comprehensively reflect general movements and trends of China A-share markets.

To further develop Chinese financial markets and provide investors with a tool to hedge risks in stock markets, the CSI 300 Index futures contract was launched on April 16, 2010 on the China Financial Futures Exchange. The expiration day of the CSI 300 index futures contact is the third Friday of the contract (delivery) month, and the contract (delivery) months include the current month, the next month, and the final months of the next two quarters, which are called quarter-months. The contract size is the index value of CSI 300 multiplied by RMB 300. As a new financial instrument, the CSI 300 index futures are under close monitoring by regulators. To open an account for stock index futures trading, domestic retail investors are required to deposit at least RMB 500,000 (approximately US$ 73,000) and pass the required qualification exam, among others. In contrast, the minimum account size for domestic institutional investors to trade the index futures is RMB 1 million (approx US$ 145,000). Therefore, the index futures trading is not suitable for most individual investors to participate, which is also explicitly mentioned in related regulatory documents issued by China Securities Regulatory Commission. Furthermore, the strict margin requirements are imposed on traders and the initial margin is 15% for the current and next month contracts, and 18% for the next two quarter-month contracts. Also, QFIIs (Qualified Foreign Institutional Investors) initially were not allowed to trade the stock index futures. These high barriers to entry imply that it is only some Chinese investors, rather than many domestic individual investors or any foreign investors, who could initially be engaged in futures trading. Thus, although the futures trading volume is impressive even compared with many other international stock index futures markets, the CSI 300 index futures price might not be as informative as that of the cash market.

Also note that the stock index futures opens a new era of confrontation between long and short sides of China's stock market. It is worthy to note in Figure 1 that the Chinese stock market had tumbled, with the benchmark CSI 300 index dropping by 27.3%, from 3,388 on April 16 to 2,463 on July 2. The sharp decline in such a short period has not been seen since the stock market price plummeted in the months during the global financial crisis in late 2007. It might or might not be a coincidence that the stock prices started falling immediately after the stock index futures were introduced. A question of interest in this study is whether there is evidence that the stock index futures prices led the falling cash market prices during the sample period.

FIGURE 1
Movements of the CSI 300 Index (cash price) and the index futures price at each time during 4/16/2010–7/30/2010.

The futures prices and underlying cash market prices, recoded at 5-min intervals, are obtained from Bloomberg. The sample period is from April 16, 2010, to July 30, 2010, as shown in Figure 1. To construct the continuous nearby futures price series, we use the intraday prices for the nearby futures contract until the contract reaches the first day of the delivery month. Then, prices for the next nearby contract are used. The nearby futures contract is used because it is highly liquid and the most active. Both the Shanghai and Shenzhen Stock Exchanges open from 9:30 a.m. to 11:30 a.m. and then from 1:00 p.m. to 3:00 p.m. (Beijing Time), while the trading hours of the CSI 300 index futures contract are from 9:15 a.m. to 11:30 a.m., and from 1:00 p.m. to 3:15 p.m. (Beijing Time). The last records of futures prices in a trading day are respectively registered at 11:25 a.m. for the morning session and 3:10 p.m. for the afternoon session. Cash and futures prices recorded before either the stock or futures exchange opens or after either of them closes are excluded, and we obtain 49 recorded cash and futures prices at five-minute intervals during each trading day. After eliminating weekends and holidays during which the trading was closed, we obtain a total of 3,528 five-minute observations. The returns of each series are calculated by taking first differences of the logarithms of prices, while the basis series is calculated as the difference between the logarithms of two series.

Panel A of Table I presents some summary statistics for the cash and futures returns and the basis. Both returns are on average negative while the basis is on average positive. Meanwhile, both cash and futures returns are similarly volatile and the basis is more volatile. The cash and futures returns are

TABLE I

Summary Statistics of the Returns, Bases, Trading Volumes, and Open Interest

Panel A: Summary Statistics for Intraday Returns and Basis

	Nobs	*Mean*	*Std*	*Skew*	*Kurt*	*Min*	*Max*
Cash return	3527	−0.000046	0.0023	−0.751	10.776	−0.024224	0.014573
Futures return	3527	−0.000052	0.0025	−0.320	15.950	−0.025822	0.019212
Basis	3528	0.010452	0.0092	1.273	2.200	−0.007738	0.044414

Panel B: Summary Statistics for Trading Activity

	Mean	Std	p1	p25	p50	p75	p99
Futures daily trading volume Nearby	161,466	134,224	6,498	19,112	130,889	296,650	392,898
Second Nearby	5,359	2,938	496	2,668	6,273	7,900	10,624
Third Nearby	1,821	1,069	385	932	1,695	2,744	4,108
Total	276,304	88,403	58,457	220,024	302,267	338,746	478,480
Open interest	21,331	8,325	3,590	14,282	23,295	29,388	33,765
Cash daily trading volume (millions)	5,041.9	1,393.8	2,771.0	3,978.7	4,927.9	5,863.2	9,596.5
Futures daily turnover (RMB billions)							
Nearby	136.638	111.145	5.014	15.852	125.157	246.46	321.995
Second Nearby	4.659	2.56	0.387	2.107	5.409	6.683	9.208
Third Nearby	1.501	0.865	0.325	0.784	1.44	2.286	3.3
Total	230.827	66.691	60.37	186.243	247.517	279.815	377.043
Cash daily turnover (RMB billions)	60.183	18.704	30.922	45.786	60.659	70.567	118.856

Note. Cash returns are the changes in the natural logarithms of the underlying CSI 300 index prices. Futures returns are the changes in the natural logarithms of the CSI 300 futures prices. The basis is the difference between futures and cash prices in the natural logarithms.

TABLE II

Trace Tests on the CSI 300 Index and Index Futures Prices

Without Linear Trend				*With Linear Trend*		
T	*C(5%)*	*Decision*	$H_o = r$	*T*	*C (5%)*	*Decision*
27.408	20.164	*R*	0	25.729	15.408	*R*
7.695	9.142	*F#*	1	7.092	3.841	*F*

Note. *r* is the number of cointegrating vectors. *T* is the trace test statistics. *C* is the trace test critical values. *R* indicates that we reject the null hypothesis that the number of cointegrating vectors is less than or equal to r (when *T* is greater that *C* (5%)). *F* indicates that we fail to reject the null hypothesis that the number of cointegrating vectors is less than or equal to *r* (when *T* is less than *C* (5%)). We stop testing at the first "*F*" (failure to reject) when starting at the top of the table and moving sequentially across from left to right and from top to the bottom. The symbol (#) indicates the stopping point.

negatively skewed, whereas the basis exhibits positive skewness. Moreover, all returns and the basis exhibit excessive kurtosis.

Panel B of Table I presents the summary statistics for trading activity for the sample. As summarized in Panel B, trading volume for the first nearby contract is greater than the second nearby contract, which in turn is greater than the third nearby contract, implying that the nearby futures contract is the most liquid and the most actively traded. Over the first three months of trading, the average daily futures trading turnover reached RMB 230.8 billion (approximately US$ 40 billion), which is more than the average daily turnover of the CSI 300 constituent stocks. In fact, the CSI 300 futures market has become one of the most actively traded futures contracts in the world. However, the open interest remains very small and on average accounts for only 7.7% of the futures trading volume, suggesting that trading volume is mainly driven by speculative day trading.

3. EMPIRICAL METHODOLOGY

This study aims to investigate price discovery and volatility transmission between the CSI 300 index and futures markets. First, the cointegration analysis is used to investigate the long-run price discovery performance of futures market. Second, an asymmetric ECM-GARCH model is employed to further investigate short-run volatility dynamics between the cash and futures markets.

3.1. Recursive Cointegration Tests

Cointegration analysis is most often conducted using the maximum likelihood estimation method of Johansen (1991). Let $X_t = \begin{pmatrix} X_{1t} \\ X_{2t} \end{pmatrix}$, where X_{1t} represents the underlying cash price in natural logarithm, and X_{2t} represents the futures price in natural logarithm. If both price series are non-stationary and cointegrated, they can be modeled by the following ECM:

$$\Delta X_t = \alpha\beta' X_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \mu + \varepsilon_t \quad (t = 1, \ldots T) \tag{1}$$

where the rank of $\Pi = \alpha\beta'$ determines the number of cointegration vectors or the cointegration rank.

In addition to the standard cointegration technique, this study further applies the recursive cointegration technique (Hansen & Johansen, 1999) to investigate the stability of the cointegration relationship (or lack of it) and constancy of some key parameters of interest. The recursive cointegration analysis may be performed under two VAR representations of model (1): the "Z-representation" and the "R-representation." In the first one, all the parameters of the model (1), including the short-run and long-run parameters, are re-estimated during the recursions, whereas in the second one, the short-run parameters Γ_i are kept fixed to their full sample values and only the long-run parameters in model (1) are allowed to be re-estimated. As suggested in Hansen and Johansen (1999), the result from the

"R-representation" would be more appropriate in recursive cointegration analysis. Thus, in what follows, we briefly describe the most relevant estimation procedure based on the "R-representation."[5]

Let $Z_{0t} = \Delta X_t$, $Z_{1t} = X_{t-1}$, $Z_{2t} = (\Delta X'_{t-1}, \ldots, \Delta X'_{t-k+1})$. For the ease of the exposition, the deterministic terms such as μ in Equation (1) can be ignored. Then, Equation (1) can be formulated as follows:

$$Z_{0t} = \alpha\beta' Z_{1t} + \Gamma Z_{2t} + \varepsilon_t \quad (t = 1, \ldots, T). \tag{2}$$

Maximum likelihood estimation of Equation (2) based on all data consists of a reduced rank regression of X_{0t} on Z_{1t} conditional on Z_{2t}. Let $R_{0t}^{(T)}$ and $R_{1t}^{(T)}$ denote, respectively, the residuals from the regression of Z_{0t} and Z_{1t} on Z_{2t} (where the superscript T denotes the case that the estimation of short-run dynamics is based on full sample data). Specifically, we have the following expressions:

$$R_{0t}^{(T)} = Z_{0t} - M_{02}^{(T)}[M_{22}^{(T)}]^{-1} Z_{2t}$$
$$R_{0t}^{(T)} = Z_{1t} - M_{12}^{(T)}[M_{22}^{(T)}]^{-1} Z_{2t}$$

where

$$M_{ij}^{t} = \sum_{s=1}^{t} Z_{it} Z'_{jt} \quad (i, j = 0, 1, 2).$$

The remaining analysis can be based on the following regression equation where the parameter Γ has been filtered out:

$$R_{0t}^{(T)} = \alpha\beta' R_{1t}^{(T)} + R_{\varepsilon t}^{(T)} \quad (t = 1, \ldots, T). \tag{3}$$

Equation (3) is called the "R-representation," which is constructed in such a way that any rejections of stability are due to changes in the long-run structure, rather than due to shifts in short-run dynamics.

Also defining the product moment matrices $S_{ij}^{T(t)}$ associated with Equation (3), the maximum likelihood estimator of the cointegrating space is determined by the solution to the eigenvalue problem as follows:

$$|\lambda S_{11} - S_{10} S_{00}^{-1} S_{01}| = 0 \tag{4}$$

which yields eigenvalues $1 > \hat{\lambda}_1 > \ldots > \hat{\lambda}_p > 0$ and $\hat{\lambda}_{p+1} = 0$. To form the basis for testing the constancy of the cointegration rank, we use the *p-r* smallest non-zero eigenvalues, $\hat{\lambda}_- = (\hat{\lambda}_{r+1}, \ldots, \hat{\lambda}_p)$, to construct the following trace test statistic:

$$Trace = -T \sum_{i=r+1}^{p} \ln(1 - \hat{\lambda}_i) \tag{5}$$

[5]The reader is referred to Hansen and Johansen (1999) for more details.

where T is the number of observations. Also, since the cointegration rank is determined by the rank of $\Pi = \alpha\beta'$, with the β parameters fixed to the estimates based on the whole sample period, the estimates of the α parameters can be obtained over time.

3.2. The Asymmetric ECM-GARCH Model

To further take account of the asymmetric effect of the basis and volatility spillover, the cash and futures returns can be jointly modeled in an asymmetric ECM-GARCH model with BEKK specification. In particular, we construct the following model:

$$\Delta X_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta X_{t-i} + \gamma \max(E_{t-1}, 0) + \eta \min(E_{t-1}, 0) + \varepsilon_t$$

$$\varepsilon_t | \Omega_{t-1} \sim D(0, H_t) \tag{6}$$

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

where

$$X_t = \begin{pmatrix} X_{1t} \\ X_{2t} \end{pmatrix},$$

X_{1t} and X_{2t} are defined as above,

$$\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}, \Gamma_i = \begin{pmatrix} \Gamma_{11} & \Gamma_{12} \\ \Gamma_{21} & \Gamma_{22} \end{pmatrix}_{-i}, \gamma = \begin{pmatrix} \gamma_1 \\ \gamma_2 \end{pmatrix}, \eta = \begin{pmatrix} \eta_1 \\ \eta_2 \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}.$$

To capture potential asymmetric effect of the basis, the basis $E_t = X_{2t} - X_{1t}$ is separated into positive and negative terms. Ω_{t-1} denotes the conditioning information set at time $t-1$,

$$H_t = \begin{pmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{pmatrix}$$

denotes the conditional covariance matrix at time t, A, B, C, G are matrices,

$$\Sigma_{t-1} = \begin{pmatrix} Max(E_{t-1}, 0) & 0 \\ 0 & -Min(E_{t-1}, 0) \end{pmatrix}$$

is the asymmetric basis matrix at time $t-1$.

Further, the information transmission through the volatility linkage is investigated by estimating the conditional covariance matrix H_t in Equation (6). There exist numerous parameterizations of the conditional covariance matrix H_t in multivariate GARCH models (Engle & Kroner, 1995). The GARCH model specification in this study extends the asymmetric BEKK specification of Kroner and Ng (1998) in that the asymmetric terms are the negative vs. positive basis (e.g. Lien & Yang, 2006, 2008), rather than negative vs.

positive return shocks. As noted earlier, we also extend Lien and Yang's (2006, 2008) models by allowing volatility spillover across markets and guaranteeing positive definiteness after allowance for asymmetric effects of the basis. Specifically, a parsimonious bivariate asymmetric GARCH (1, 1)-BEKK specification is adopted as follows:

$$\begin{aligned} H_t = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{bmatrix} &= \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}' \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix} \\ &+ \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' \begin{bmatrix} \varepsilon^2_{1,t-1} & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \\ &+ \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}' \begin{bmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \\ &+ \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} Max(E_{t-1}, 0) & 0 \\ 0 & -Min(E_{t-1}, 0) \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}. \end{aligned} \tag{7}$$

To see how the last term of asymmetric basis effects still guarantees a positive definite conditional covariance matrix, the alternative expression after the matrix multiplication can be written as follows:

$$\begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} Max(E_{t-1}, 0) & 0 \\ 0 & -Min(E_{t-1}, 0) \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}$$

$$\begin{bmatrix} g^2_{11}Max(E_{t-1}, 0) - g^2_{21}Min(E_{t-1}, 0) & g_{11}g_{12}Max(E_{t-1}, 0) - g_{21}g_{22}Min(E_{t-1}, 0) \\ g_{11}g_{12}Max(E_{t-1}, 0) - g_{21}g_{22}Min(E_{t-1}, 0) & g^2_{12}Max(E_{t-1}, 0) - g^2_{22}Min(E_{t-1}, 0) \end{bmatrix}. \tag{8}$$

It is clear that the volatilities, diagonal elements in the conditional covariance matrix, are positive, as reflected in the positive diagonal elements in Equation (8). Moreover, by construction, the specification in Equation (8) is consistent with the stylized fact documented by Kogan et al. (2009), who find a V-shape relationship between the volatility of futures prices and the slope of the forward curve or the basis. That is to say, asymmetric basis effect on futures volatility is positive (negative) when the basis is positive (negative). More specifically, the positive effect of the positive basis on futures volatility is measured by g^2_{12} and the negative effect of the negative basis on futures volatility is measured by $-g^2_{22}$. Thus, we can test the prediction of Kogan et al. (2009) by examining the statistical significance of parameters g_{12} and g_{22}. Similarly, g^2_{11} ($-g^2_{21}$) measures the positive (negative) basis effect on cash market volatility and the products of parameters and $g_{11}g_{12}$ ($-g_{21}g_{22}$) measures the positive (negative) basis effects on conditional covariance. In addition, the positive and negative basis effects on returns are captured by γ and η, respectively. When the basis is positive (negative), the cash price tends to be increasing (decreasing) whereas the futures price tends to be decreasing (increasing) in the next period to maintain their long-term relationship, therefore we predict that both γ_1 and η_1 are positive, while both γ_2 and η_2 are negative.

Equation (8) is estimated simultaneously by using the maximum likelihood estimation procedure. With the above specification, we can use off-diagonal parameters in matrices A and B to explain volatility spillover effect. The off-diagonal parameter a_{12}^2 (a_{21}^2) measures the transmission of the absolute size of the return shocks, as measured by squared values of lagged unpredictable returns, originating from the cash (futures) market in the previous period to the current period's conditional volatility in the futures (cash) market, while the dependence of the conditional volatility in the futures (cash) market on that of the cash (futures) market in the previous period is measured by the parameter b_{12}^2 (b_{21}^2).[6]

Nevertheless, not all the channels of volatility spillovers can be exhaustively taken into account in the above specification, so such interpretation on the off-diagonal parameters, though perhaps revealing, should be considered preliminary. Unfortunately, the interpretation of other parameters from the GARCH-BEKK model is generally not straightforward. Following the literature (e.g. Darbar & Deb, 1997; Fleming, Kirby, & Ostdiek, 1998), we use the time-varying cross-market conditional correlation, computed as $CC_t = h_{12,t}/(h_{11,t}h_{22,t})^{1/2}$, to gauge the volatility linkage across the markets.

4. EMPIRICAL RESULTS

4.1. Results on Price Discovery

As the first stage in our empirical analysis, the order of integration of the time series is determined. To this end, standard unit root procedures, i.e. Augmented Dickey–Fuller and Phillips–Perron tests, are applied to examine time series properties of the data. Consistent with the literature, the results show that the null hypothesis of a unit root is not rejected for level series, but is strongly rejected for first-differenced series at conventional significance levels.[7]

Therefore, it can be concluded that the cash and futures prices under consideration are well characterized as non-stationary or I(1) processes. The Johansen's (1991) procedure is then applied to test for cointegration between the series. Specifically, the optimal lags for level VAR are selected based on the

[6]Such an interpretation would be more obvious if one looks at the alternative expression after the matrix multiplication. See Engle and Kroner (1995, p 127) for the specific BEKK model specification used in this study.
[7]To save the space, the results of unit root tests are not reported here, but are available on request.

Akaike Information Criterion (AIC), and conduct the Johansen (1991) trace test for cointegration. It is well known that the determination of the cointegration rank depends on how μ in Equation (1) enters into the ECM—either as a constant in the cointegrating vector or as a time trend in the original levels representation. To deal with this problem, a sequential hypothesis testing procedure proposed by Johansen (1992) is followed. If there is a linear trend in the model, the hypothesis is labeled $H_0(r)$, which is an unrestricted case. If there is no linear trend in the model, the hypothesis is labeled $H_0(r)^*$, which is restricted. According to the sequential hypothesis testing procedure, hypotheses are tested in the following order: $H_0(0)^*$, $H_0(0)$, $H_1(1)^*$, $H_1(1) \ldots H_1(p)^*$, and $H_1(p)$. When the null hypothesis first fails to be rejected in the sequence, testing is stopped and the associated null hypothesis is accepted. The trace test statistics of Johansen's (1991) summarized in Table II indicate the existence of one cointegrating vector between cash and future prices without the presence of a linear trend in the data.

To further take into account the possible structural breaks in the long-run relationship between cash and futures prices, the recursive cointegration technique is applied to reveal the (in)stability of the identified (non) cointegration relationship. The normalized trace tests are shown in Figure 2, which are calculated at each data point over the period from May 10 through July 30, 2010. The first 15-day period (a total of 735 observations) is used as the initial estimation period. Since the statistics in the figure are normalized by the 5% critical values, if figure entries are greater than 1.0, then we can reasonably reject the null hypothesis at that data point. From Figure 2, a serious disconnect between the two markets is found during the first two months of the futures trading, because it is clear that no cointegration exists until the June 17, though a very short peak goes beyond the line 1.0 at the beginning of the recursive period. This conclusion is reached irrespective of the choice of the R-representation or the Z-representation.

According to the discussion in Brenner and Kroner (1995) and Yang, Bessler, and Leatham (2001), there are two necessary conditions for the unbiasedness hypothesis. The first is cointegration between the cash and futures prices, which has been confirmed by the results of the Johansen (1991) test. The second can be formulated as statistical tests with respect to the cointegrating vector $\beta = (\beta_1\ \beta_2) = (1\ -1)$. Hence, we proceed to conduct a likelihood-ratio (LR) test of this restriction. The results shown in Table III indicate that the hypothesis cannot be rejected, which also justifies the use of the basis as a stationary variable in the earlier studies.

As pointed out in Yang, Bessler, and Leatham (2001) and Zhong et al. (2004), the long-run prediction hypothesis can be tested based on the adjustment coefficients. If the hypothesis of $\alpha_2 = 0$ ($\alpha_1 = 0$) cannot be rejected, the futures (cash) price leads the cash (futures) price in the long run, however,

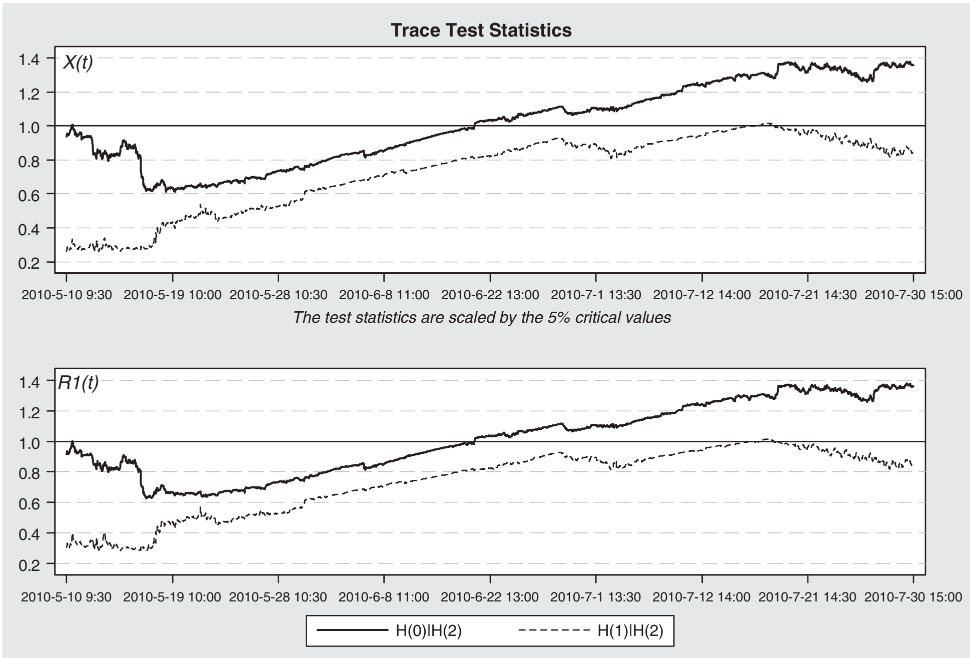

FIGURE 2
Trace test statistics on cointegration between the CSI 300 Index and index futures prices at each time during 4/16/2010–7/30/2010.

when $\alpha_1 \neq 0$ and $\alpha_2 \neq 0$ cannot be rejected, there is a bidirectional information flow in the long run between cash and futures prices.[8] Following the suggestion in Zapata and Rambaldi (1997), the prediction hypothesis is also tested jointly with the restrictions readily imposed by the unbiasedness hypothesis. With the above restrictions on β imposed, the results reported in Table III render strong evidence in favor of weak exogeneity of the cash price, suggesting the leading long-run information role of the cash market.

Parameter constancy tests are also further conducted to examine the stability of the adjustment between cash and futures markets. With the restriction $\beta = (\beta_1\ \beta_2) = (1\ -1)$ imposed, the recursively calculated adjustment coefficients and associated t-statistics for both markets are shown in Figure 3. Consistent with the results in Table III, these two graphs reveal that at each point of time the adjustment to the deviation from the long-run relationship is solely carried out on the futures market rather than the cash market, implying that the cash market leads the futures market in the long run.

[8]Eun and Sabherwal (2003) also makes a similar argument in the context of the price discovery between cross-listed stocks in the United States and Canada. Also note that the popular Gonzalo-Granger common factor weights are solely determined by α_1 and α_2 in the bivariate case (see Gonzalo and Granger (1995) for more details).

TABLE III
Hypothesis Testing on Cointegrating Space

	Restriction Testing				
Unrestricted Estimates	*Hypothesis*	χ^2	*d.f.*	*Result*	*Restricted Estimates*
$\beta' = (1–1.000–0.008)$	$\beta_1 + \beta_2 = 0$	0.000	1	*F*	$\beta' = (1–1.000–0.008)$
	$\beta_1 + \beta_2 = 0\ \beta_0 = 0$	6.342	2	*R*	
	$\beta_1 + \beta_2 = 0\ a_1 = 0$	0.830	2	*F*	$\beta' = (1-1.000-0.008)\ \alpha' = (0.0.012)$
	$\beta_1 + \beta_2 = 0\ a_2 = 0$	11.747	2	*R*	

Note. The notation $b' = (\beta_1\ \beta_2$ constant) is used in Equations (1) and (6). *R* indicates that we reject the null hypothesis and *F* indicates that we fail to reject the null hypothesis at the 0.05 significance level.

Overall, the results based on cointegration analysis provide strong evidence that the cash market leads the futures market in transmitting long-run information and the cash market dominates the futures market in price discovery. This is perhaps not too surprising, given the fact that many domestic individual investors and foreign investors were practically prevented from trading in the futures markets by the stringent regulations as discussed above, and such high barriers to entry reduces the information content of the futures prices and thus the emerging futures market's price discovery performance.

To determine if the above model is correctly specified, a battery of diagnostic tests are performed on the standardized residuals from the aforementioned estimation. In particular, Ljung-Box Q statistics are used to test the null hypothesis of no autocorrelations of the residuals. The result indicates that there is no autocorrelation in the standardized residuals and the model is quite well specified. However, the presence of unexplained ARCH effect is detected in the standardized residuals. It should be noted that the above results focus on cointegration analysis and parameters related to the long-run structure, and have not yet adequately addressed the short-run dynamics between the cash and futures market, particularly when GARCH effects should be further taken into account.

4.2. Results on Volatility Transmission

To address the issue further, the bivariate asymmetric ECM-GARCH model is estimated and the results are summarized in Table IV. As discussed above, the pattern of information transmission through volatility can be investigated by examining estimates of off-diagonal parameters a_{12}, a_{21}, b_{12}, and b_{21}. The result provides strong evidence in favor of two-way volatility transmission between the cash market and the futures market, since a_{12}, a_{21}, and b_{12} are statistically

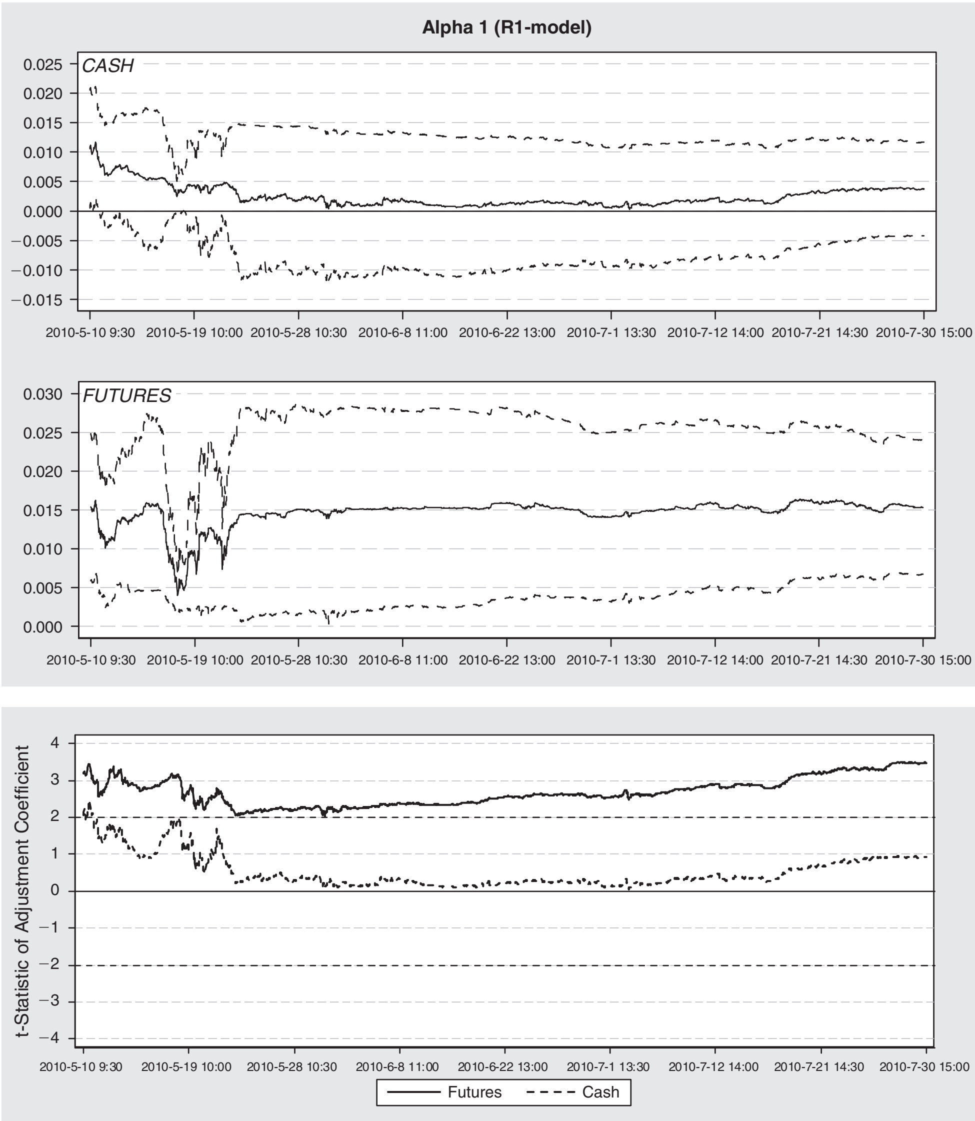

FIGURE 3
Recursive estimates of adjustment coefficients (and their upper and lower bounds) and associated *t*-statistics to the cointegration vector between the CSI 300 Index and index futures prices at each time during 4/16/2010–7/30/2010.

significant. On one hand, the parameter which measures the cross-market impact of returns shocks on the volatility, a_{12}, is statistically significant, suggesting the conditional volatility in the futures market depends on return shocks from the cash market in the previous period. On the other hand, as the parameter a_{21} is statistically significant, the return shocks from the futures market in the previous period impact the current conditional volatility in the

TABLE IV
Asymmetric ECM-GARCH Model Estimation Results

	Parameters	*t-Ratios*
Mean equations		
$(\Gamma_{11})_{-1}$	−0.398	(−16.128)***
$(\Gamma_{11})_{-2}$	−0.131	(−4.793)***
$(\Gamma_{11})_{-3}$	−0.059	(−2.827)***
$(\Gamma_{12})_{-1}$	0.473	(17.646)***
$(\Gamma_{12})_{-2}$	0.177	(6.507)***
$(\Gamma_{12})_{-3}$	0.074	(2.955)***
γ_1	−0.003	(−0.503)
η_1	0.012	(0.403)
$(\Gamma_{21})_{-1}$	−0.009	(−0.292)
$(\Gamma_{21})_{-2}$	0.065	(1.918)
$(\Gamma_{21})_{-3}$	0.035	(1.345)
$(\Gamma_{22})_{-1}$	−0.105	(−3.498)***
$(\Gamma_{22})_{-2}$	−0.084	(−2.587)***
$(\Gamma_{22})_{-3}$	−0.009	(−0.388)
γ_2	−0.013	(−2.343)**
η_2	0.007	(0.261)
Variance equation		
a_{11}	−1.348	(−21.027)***
a_{12}	−1.075	(−10.214)***
a_{21}	1.133	(10.149)***
a_{22}	1.496	(43.671)***
b_{11}	0.259	(3.540)***
b_{12}	0.031	(0.456)
b_{21}	−0.314	(−5.046)***
b_{22}	0.065	(1.242)
g_{11}	0.006	(5.898)***
g_{12}	0.004	(4.484)***
g_{21}	0.000	(0.000)
g_{22}	0.000	(0.000)
CC_t	77.7%	(503.474)***

Note. "***" and "**"denote statistical significance at the 1 and 5% levels, respectively. To conserve the space, some less relevant parameter estimates (e.g. the constant) are omitted.

cash market. Furthermore, the conditional volatility in the cash market depends on that of the futures market in the previous period, as reflected in the significance of the parameter b_{12}.

To gauge the volatility linkage across the markets, the conditional correlation between the cash and futures returns is also calculated and the mean statistic of estimated conditional correlation is reported in Table IV. The results suggest intensive volatility transmission between the cash and futures markets, as shown by the high mean conditional correlation (77.7%). In sum, the results indicate strong bidirectional dependence in the intraday volatility of both markets, suggesting that volatility information originated in either the stock or the futures markets are transmitted to the other market. These findings are consistent with some earlier studies (e.g. Chan et al., 1991), but only partly consistent with many others (e.g. Kavussano, Visvikis, & Alexakis, 2008).

The results reported in Table IV also indicate asymmetric effects of basis. The futures return displays a negative response to an increased positive basis, as reflected in the insignificance of all the four relevant parameters except γ_2. The evidence here shows that only the futures price adjusts itself toward the long-term equilibrium and tends to be decreasing when the futures price exceeds the cash price, which further confirms the finding above. In terms of the asymmetric basis effects on volatilities, inspection of all four relevant parameters reveals that only g_{11} and g_{12} are statistically significant, suggesting that only positive lagged basis has a significant positive effect on the volatilities of both markets and their conditional covariance, which is partly consistent with the findings in the theoretical work of Kogan et al. (2009) and the empirical work of Lien and Yang (2006, 2008). In addition, the numerical comparison indicates $g_{11}^2 > g_{12}^2$, suggesting that the positive lagged basis has a larger positive impact on the volatilities of cash market than that of futures market.

A plausible explanation for the documented asymmetric basis effect may go as follows. As investors are subject to serious short sale constraints in the Chinese stock market (but not in Chinese stock index futures market), index arbitrageurs between the Chinese stock index and stock index futures find it easier to take actions when the futures price lies above its fair value (leading to a more positive basis), which requires going short the index futures contract and long the index, than when the futures price is below its fair value (leading to a more negative basis), which requires shorting the index and going long the futures. Therefore, one would expect the positive lagged basis to have a more pronounced impact on the cash market's volatility than the negative lagged basis, simply because index arbitrageurs cannot implement the arbitrage effectively when futures are underpriced.

4.3. Robustness Checks

To check the robustness of the main findings presented previously, the continuous futures price series is re-constructed and the ECM-GARCH model is re-estimated. In particular, the futures prices are re-constructed using the following different methods: (1) while the price and return series are still constructed as described in section 2, the overnight returns are now discarded as they span a different time interval from five minutes. To further take account of potential stale opening cash market prices, the first two 5-minute returns on each trading day are also excluded; (2) consistent with McMillan and Speight (2006), the nearest-to-maturity contract is used always, switching to the next nearby contract when traded volume in the second nearest contract exceeds

TABLE V
Results of Robustness Check

	First		*Second*		*Third*	
	Parameters	*t-ratios*	*Parameters*	*t-Ratios*	*Parameters*	*t-ratios*
	Mean Equations		*Mean Equations*		*Mean Equations*	
$(\Gamma_{11})_{-1}$	−0.400	(−15.919)***	−0.388	(−15.895)***	−0.392	(−13.694)***
$(\Gamma_{11})_{-2}$	−0.095	(−3.594)***	−0.128	(−4.768)***	−0.133	(−4.796)***
$(\Gamma_{11})_{-3}$	−0.008	(−0.413)	−0.057	(−2.364)**	−0.059	(−2.513)**
$(\Gamma_{12})_{-1}$	0.475	(18.119)***	0.485	(17.819)***	0.481	(16.984)***
$(\Gamma_{12})_{(2}$	0.154	(6.502)***	0.177	(6.780)***	0.180	(6.498)***
$(\Gamma_{12})_{-3}$	0.040	(1.983)**	0.070	(2.749)***	0.075	(2.948)***
γ_1	0.005	(1.501)	−0.003	(−0.503)	0.001	(0.172)
η_1	0.015	(0.682)	0.038	(1.288)	0.003	(0.117)
$(\Gamma_{21})_{-1}$	−0.051	(−1.853)	−0.027	(−0.925)	−0.013	(−0.407)
$(\Gamma_{21})_{-2}$	0.042	(1.530)	0.022	(0.646)	0.045	(1.424)
$(\Gamma_{21})_{-3}$	0.039	(1.477)	0.047	(1.573)	0.053	(1.750)
$(\Gamma_{22})_{-1}$	−0.109	(−4.014)***	−0.090	(−2.858)***	−0.094	(−2.658)***
$(\Gamma_{22})_{-2}$	−0.060	(−2.141)**	−0.056	(−1.804)*	−0.071	(−2.605)***
$(\Gamma_{22})_{-3}$	−0.006	(−0.246)	−0.023	(−0.825)	−0.024	(−0.838)
γ_2	−0.006	(−2.003)**	−0.016	(−2.538)***	−0.017	(−3.042)***
η_2	−0.002	(−0.108)	0.017	(0.518)	−0.010	(−0.334)
	Variance equation		Variance equation		Variance equation	
a_{11}	0.219	(1.109)	0.090	(0.500)	0.091	(0.375)
a_{12}	−0.304	(−2.082)**	−0.407	(−17.120)***	−0.463	(−1.804)
a_{21}	0.407	(4.802)***	0.550	(7.970)***	0.522	(4.037)***
a_{22}	1.104	(15.853)***	1.213	(61.870)***	1.237	(9.615)***
b_{11}	0.201	(2.901)***	−0.213	(−3.486)***	−0.200	(−2.336)**
b_{12}	0.141	(2.033)**	−0.014	(−0.227)	−0.021	(−0.204)
b_{21}	−0.244	(−5.203)***	0.391	(6.433)***	0.344	(4.620)***
b_{22}	0.137	(2.195)**	−0.054	(−0.917)	−0.036	(−0.407)
g_{11}	−0.008	(−10.297)***	0.010	(8.715)***	−0.010	(−4.872)***
g_{12}	−0.003	(−3.397)***	0.003	(2.362)**	−0.004	(−1.438)
g_{21}	0.000	(0.000)	0.007	(0.819)	0.000	(−0.005)
g_{22}	0.000	(0.000)	0.003	(0.746)	0.000	(−0.005)
CC_i	75.2%	(419.944)***	77.5%	(486.764)***	77.8%	(611.874)***

Note. The robustness checks repeat the estimation of ECM-GARCH model. In the first robustness check, the price and return series are constructed as described in Section 2, however, the overnight returns and the first two 5-min returns are excluded; in the second robustness check, to re-construct the continuous futures price series, the nearest-to-maturity contract is used always, switching to the next nearby contract when traded volume in the second nearest contract exceeds that in the nearest-to-maturity contract. In the third robustness check, the nearest-to-maturity contract is used always, switching to the next nearby contract five days before expiration. "***" and "**" denote statistical significance at the 1 and 5% levels, respectively. To conserve the space, some less relevant parameter estimates (e.g. the constant) are omitted.

that in the nearest-to-maturity contract; (3) following Chen and Gau (2009, 2010), the most actively traded nearest-to-maturity contract is used, with the switch to the next nearby contract five days before the expiration date.

Table V summarizes the re-estimates of the ECM-GARCH model on the newly constructed data. From Table V, it is obvious that statistical significances of the key parameters are very similar to those reported in Table IV, and the inferences are essentially the same. In the first robustness, the regression coefficient of γ_2 is significantly negative at the 5% level, while other three parameters are not statistically significant. Therefore, it is the futures price, and not the cash price, that adjusts itself toward the long-term equilibrium, which is consistent with the findings above. Also, the evidence for existence of a two-way volatility transmission between both markets is robust, as shown by significant estimates of a_{12}, a_{21}, b_{12}, and b_{21} reported in Table V. Again, both coefficients of g_{11} and g_{12} are statistically significant, indicating that the lagged basis has impacts on the volatilities of both markets and their conditional covariance. Furthermore, the mean statistic of estimated conditional correlation is very high and close to that reported in Table IV, which confirms that there is significant volatility transmission between both markets. Furthermore, with an exception that the coefficient a_{12} is significant at the 10% level but not at the 5% level or lower in the third robustness check, the second and third robustness checks also yield basically the similar conclusions, and therefore confirm the robustness of the main findings.

5. CONCLUSIONS

Using intraday high-frequency data, this study, for the first time to our knowledge, investigates intraday price discovery and volatility transmission between the Chinese stock index and the newly established stock index futures markets in China. Although the Chinese stock index started a sharp decline immediately after the stock index futures were introduced, we find that the cash market plays a more dominant role in the price discovery process. The new stock index futures market does not function well in its price discovery performance at its infancy stage. A possible explanation for the finding is that higher barriers to entry, which practically exclude many informed traders including many domestic individual investors and foreign investors, result in weakened price discovery ability. The finding is different from many previous studies reviewed in Brenner and Kroner (1995) and Yang, Bessler, and Leatham (2001), but is consistent with recent findings on currency futures markets (e.g. Cabrera, Wang, & Yang, 2009; Chen & Gau, 2010; Rosenberg & Traub, 2009), where currency cash markets overshadows currency futures markets in the size and trading volume and thus take the leading role in price discovery. Furthermore, this finding is also in line with that of Chen and Gau (2009), who show that the stock index contributes more to price discovery than index futures and index options in Taiwan. In addition, the results indicate strong bidirectional intraday volatility dependence in these two markets, suggesting that the volatility originated in either the Chinese stock or futures markets would transmit to the other.

In sum, China's emerging futures market is not informationally dominant at its infancy stage of development. In this sense, the stock index futures did not play a primary role in leading the drastic drop of the cash market price.

Finally, the results suggest that only the positive lagged basis has a significant positive effect on the volatilities of both markets and their conditional covariance, which is consistent with the theoretical prediction of Kogan et al. (2009) and the short sale constraint of stocks in China. It is also documented that the positive lagged basis has a larger positive impact on the volatilities of the cash market than that of the futures market.

Future research may be fruitful to examine many other aspects of the important Chinese stock index futures market, including revisiting the issues under study in this study when the market is more developed with lower barriers to entry and changes of the regulation. It is also interesting to obtain futures trading records and study behaviors of individual and/or institutional investors (e.g. Liu, Tsai, Wang, & Zhu, 2010; Ng & Wu, 2007).

BIBLIOGRAPHY

Abhyankar, A. H. (1995). Return and volatility dynamics in the FT-SE 100 stock index and stock index futures markets. Journal of Futures Markets, 15, 457–488

Bailey, W. (1994). Risk and return on China's new stock markets: Some preliminary evidence. Pacific-Basin Finance Journal, 2, 243–260.

Bhar, R. (2001). Return and volatility dynamics in the spot and futures markets in Australia: An intervention analysis in a bivariate EGARCH-X framework. Journal of Futures Markets, 21, 833–850.

Brenner, R. J., & Kroner, K. F. (1995). Arbitrage, cointegration, and testing the unbiasedness hypothesis in financial markets. Journal of Financial and Quantitative Analysis, 30, 23–42.

Cabrera, J. F., Wang, T., & Yang, J., (2009). Do futures lead price discovery in electronic foreign exchange markets? Journal of Futures Markets, 29, 137–156.

Chan, K. (1992). A further analysis of the lead–lag relationship between the cash market and stock index futures market. Review of Financial Studies, 5, 123–152.

Chan, K., Chan, K. C., & Karolyi, G. A. (1991). Intraday volatility in the stock index and stock index futures markets. Review of Financial Studies, 4, 657–684.

Chan, K. C., Fung, H. G., & Leung, W. K., (2004). Daily volatility behavior in the Chinese futures markets. Journal of International Financial Markets, Institutions and Money, 14, 491–505.

Chatrath, A., Christie-David, R., Dhanda, K., & Koch, T. (2002). Index futures, leadership, basis behavior, and trader selectivity. Journal of Futures Markets, 22, 649–677.

Chen, Y. L., & Gau, Y. F. (2009). Tick sizes and relative rates of price discovery in stock, futures, and options markets: Evidence from the Taiwan stock exchange. Journal of Futures Markets, 29, 74–93.

Chen, Y. L., & Gau, Y. F. (2010). News announcements and price discovery in foreign exchange spot and futures markets. Journal of Banking and Finance, 34, 1628–1636.

Darbar, S. M., & Deb, P. (1997). Co-movements in international equity markets. Journal of Financial Research, 20, 305–322.
Engle, R. F., & Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric Theory, 11, 122–150.
Eun, C. S., & Sabherwal, S. (2003). Cross-border listings and price discovery: Evidence from US-listed Canadian stocks. Journal of Finance, 58, 549–575.
Fleming, J., Kirby, C., & Ostdiek, B. (1998). Information and volatility linkages in the stock, bond and money markets. Journal of Financial Economics, 49, 111–137.
Fleming, J., Ostdiek, B., & Whaley, R. (1996). Trading costs and the relative rates of price discovery in stock, futures and options markets. Journal of Futures Markets, 16, 353–387.
Fung, H. G., Liu, Q., & Tse, Y. M. (2010). The information flow and market efficiency between the US and Chinese copper and aluminum futures markets. Journal of Futures Markets, 30, 1192–1209.
Ghosh, A. (1993). Cointegration and error correction models: Intertemporal causality between index and futures prices. Journal of Futures Markets, 13, 193–198.
Gonzalo, J., & Granger, C. W. J. (1995). Estimation of common long-memory components in cointegrated systems. Journal of Business and Economic Statistics, 13, 27–36.
Hansen, H., & Johansen, S. (1999). Some tests for parameter constancy in cointegrated VAR models. Econometrics Journal, 2, 306–333.
Hodgson, A., Masih, A., & Masih, R. (2003). Price discovery between informationally linked markets during different trading phases. Journal of Financial Research, 26, 77–96.
Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. Econometrica, 59, 1551–1580.
Johansen, S. (1992). Determination of cointegration rank in the presence of a linear trend. Oxford Bulletin of Economics and Statistics, 54, 383–397.
Kavussano, M. G., Visvikis, I. D., & Alexakis, P. D. (2008). The lead-lag relationship between cash and stock index futures in a new market. European Financial Management, 14, 1007–1025.
Kogan, L., Livdan, D., & Yaron, A. (2009). Oil futures prices in a production economy with investment constraints. Journal of Finance, 64, 1345–1375.
Kroner, K. F., & Ng, K. V. (1998). Modeling asymmetric comovements of asset returns. Review of Financial Studies, 11, 817–844.
Lee, T. (1994). Spread and volatility in spot and forward exchange rates. Journal of International Money and Finance, 13, 375–383.
Lee, K. C., Fung, H. G., & Liao, T. L. (2009). Day-of-the-week Effects in the US and Chinese Commodity Futures Markets. Review of Futures Markets, 18 (Summer), 27–53.
Lien, D., & Yang, L. (2006). Spot-futures spread, time-varying correlation, and hedging with currency futures. Journal of Futures Market, 26, 1019–1038.
Lien, D., & Yang, L. (2008). Asymmetric effect of basis on dynamic futures hedging: Empirical evidence from commodity markets. Journal of Banking and Finance, 32, 187–198.
Liu, Y. J., Tsai, C. L., Wang, M. C., & Zhu, N. (2010). Prior consequences and subsequent risk taking: New field evidence from the Taiwan futures exchange. Management Science, 56, 606–620.

McMillan, D. G., & Speight, A. E. H. (2006). Nonlinear dynamics and competing behavioral interpretations: Evidence from intra-day FTSE-100 index and futures data. Journal of Futures Markets, 26, 343–368.

Miller, E. M. (1977). Risk, uncertainty and divergence of opinion. Journal of Finance, 32, 1151–1168.

Ng, V., & Pirrong, S. C. (1994). Fundamentals and volatility: Storage, spreads, and the dynamics of metals prices. Journal of Business, 67, 203–230.

Ng, L., & Wu, F. (2007). The trading behavior of institutions and individuals in Chinese equity markets. Journal of Banking and Finance, 31, 2695–2710.

Rosenberg, J., & Traub, L. G. (2009). Price discovery in the foreign currency futures and spot market. Journal of Derivatives, 17(2), 7–25.

Stoll, H. R., & Whaley, R. E. (1990). The dynamics of stock index and stock index futures returns. Journal of Financial and Quantitative Analysis, 25, 441–468.

Yang, J., Bessler, D. A., & Leatham, D. J. (2001). Asset storability and price discovery of commodity futures markets: A new look. Journal of Futures Markets, 21, 279–300.

Zapata, H. O., & Rambaldi, A. N. (1997). Monte Carlo evidence on cointegration and causation. Oxford Bulletin of Economics and Statistics, 59, 285–298.

Zhong, M., Darrat, A. F., & Otero, R. (2004). Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico. Journal of Banking and Finance, 28, 3037–3054.