Price Discovery in the CSI 300 Index Futures and Spot Markets: An Empirical Analysis Using High-Frequency Data in China

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Business and Economics Honors Program

NYU Shanghai

May 2025

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Content

Abstract

This thesis investigates the price discovery relationship between the CSI 300 index futures and its underlying spot index in the Chinese financial market, using five-minute high-frequency data from 2024 January to 2024 December. While index futures are typically viewed as leading instruments in global markets, it remains unclear whether this leadership extends to China's relatively young and regulated futures market. To addressing this gap and provide a new perspective using high-frequency data, this thesis aims to determine whether CSI 300 futures play a dominant role in reflecting new information, and to quantify their contribution to price discovery relative to the spot market. I begin by testing for unit roots and cointegration to confirm the long-run equilibrium between the two markets. Using a vector error correction model (VECM) and Granger causality analysis, I find strong evidence that futures prices significantly Granger-cause spot prices. To further quantify this leadership, I apply Information Share model, which reveals that the CSI 300 futures market contributes the majority share of information to the common efficient price. These findings confirm that China's index futures market, despite structural constraints and regulatory oversight from 2015 to 2018, has evolved into an effective and efficient venue for price discovery. This study contributes to the growing literature on market microstructure in emerging economies and offers important implications for policymakers, investors, and financial institutions regarding the informational efficiency and utility of index futures in China.

Keywords: price discovery; Chinese financial market; CSI 300 index futures; high-frequency data; vector error correction model; information share model

1. Introduction

The primary role of the futures market is to incorporate information and reflect the price of the underlying asset. Price discovery is the process through which markets incorporate new information into asset prices, and it plays a critical role in ensuring market efficiency. In developed economics, index futures have long been seen as tools for investors to hedge risks and express market expectations, which can lead spot prices in assimilating new information. However, in China, the history of index futures is quite short, and the role of futures in the price discovery process remains less well understood, due to distinctive regulatory frameworks, trading restrictions, and historical segmentation between the spot and futures markets.

The CSI300 index, which comprises the top 300 A-share stocks listed on the Shanghai and Shenzhen Stock Exchanges, is a widely recognized benchmark for the Chinese equity market. Its corresponding futures contract – CSI300 stock index futures – began to trade on the China Financial Futures Exchange (CFFEX) in April 2010. Since then, it has become increasingly liquid and serves as a key instrument for institutional investors. However, in 2015 September, due to dramatic decrease in the Chinese stock market, the China Securities Regulatory Commission (CSRC) imposed substantial regulations and restrictions on futures trading. The new rules limited the daily transaction volume of the futures market and thus, the futures trading drop dramatically. The regulation was loosened in 2018 and afterwards the Chinese futures market experienced another period of rapid development. Later on, SSE50 index futures and CSI500 index futures were launched in 2015 and 2021, respectively. In 2024, the total trading volume of Chinese futures market reached 7.729 billion contracts, and the cumulative turnover reached 619.26 trillion yuan.

In this paper, I will mainly focus on the price discovery function of CSI300 index futures. Since its inception, there have been much research on the price discovery function of it. I will summarize these papers in the Literature Review section. My contributions to this area are that firstly, I filled the research gap after 2020, since I want to mainly investigate after 2015 Restriction Period and 2020 Covid Period, what is the efficiency of the index futures market in China. And secondly, I use 5-min high frequency data to provide a more precise and detailed analysis of the price discovery function of CSI300 index futures.

To conduct my research, I employ a combination of cointegration analysis, vector error correction models (VECM), Granger causality tests, and Information Share model. I assess both the long-term equilibrium and short-term dynamics between the two markets.

2. Literature Review

2.1 Theoretical Foundations of Price Discovery

Price discovery refers to the process through which markets incorporate new information into asset prices, and is fundamental to the concept of market efficiency. Zeckhauser and Niederhoffer (1983) were among the first to observe a significant premium between index futures and their underlying stock indices, highlighting the predictive power of futures prices over spot prices. Since then, the role of the futures market in enhancing information transmission and reducing noise in asset pricing has been extensively theorized. Scholars such as Bray (1981), Danthine (1978), and Stoll and Whaley (1988) argued that futures markets contribute to price discovery through improved information delivery mechanisms, thereby stabilizing the underlying spot market.

Hasbrouck (1995) and Gonzalo and Granger (1995) provided seminal methodological tools to quantify the information share of each market in the price discovery process. Hasbrouck's Information Share (IS) model and Gonzalo-Granger's Common Factor Weighting approach became dominant frameworks in decomposing price innovations into market-specific components. These tools have enabled scholars to empirically assess how efficiently futures markets incorporate public information relative to their spot counterparts.

2.2 Empirical Evidence from Developed Markets

It is well documented in the literature through many empirical studies in developed markets that futures markets act as a leading market in price discovery process over their corresponding spot markets. Kawaller, Koch, and Koch (1987), Grünbichler, Longstaff, and Schwartz (1994), and Stoll and Whaley (1990) demonstrated that futures prices react more quickly to new information than spot prices. The explanation for this latter leadership is that the transaction costs are lower, there is higher leverage, less regulation, and futures markets have greater liquidity.

Chan (1992) showed strong evidence that S&P 500 index futures are efficient at leading the underlying spot market. Similarly, Pizzi et al. (1998) reported that E-mini futures played a dominant role in price formation relative to their cash counterparts. Empirical studies on other mature markets, such as the FTSE 100 (Brooks et al., 2001), DAX (Booth et al., 1999), Nikkei 225 (Covrig et al., 2004), and the Mexican market (Zhong et al., 2004), also supported the view that index futures play a critical role in absorbing and disseminating market-relevant information.

Despite this consensus, some studies have identified periods of bi-directional or even reversed causality. For instance, Cabrera, Wang, and Yang (2009) and Yang, Yang, and Zhou (2012) found that, under certain conditions the spot market may also lead or simultaneously adjust with the futures market. These results suggest that price discovery dynamics may not be static but vary across time, market conditions, and asset types.

2.3 Volatility Spillovers and Alternative Explanations

In addition to pure lead-lag analysis, a number of papers investigate the link between volatility and information flow. French and Roll (1986) and Ross (1989) argue that it can be possible to use volatility as a proxy for the arrival rate of information so that the market with higher volatility is the more efficient for price discovery. According to the stabilization hypothesis, futures markets stabilize the spot markets, since they allow for hedging and information asymmetry decreases (Barber et al., 2001; Danthine, 1978). On the other hand, the destabilization theory, typically associated with developing markets, posits that futures trading can lead to increased instability in the spot markets as a result of the speculative activity and lower level of investors' sophistication (Cox and Peterson, 1994; Kasman and Kasman, 2008).

Chakravarty, Gulen, and Mayhew (2004) further highlight the role of trading volume and spreads in determining which market dominates in price discovery. Their research links microstructural factors—such as liquidity and informed trading—to macro-level outcomes like volatility and efficiency.

2.4 Price Discovery in Emerging Markets and China

Although developed markets exhibit a rather consistent dominance of futures in price discovery, emerging markets provide mixed findings. Researchers have examined this question in diverse contexts, including Thailand (Judge and Reancharoen, 2014), South Korea (Kang, Cheong, and Yoon, 2013), and Mexico (Zhong et al., 2004). They all produce different results because of varying market maturity, trading mechanisms, and regulatory setting.

In China, the CSI 300 index futures are a milestone in the country's financial derivatives market development. The earliest attempt to investigate its price discovery role was made by Yang, Yang and Zhou (2012) and there was only limited evidence of futures leadership in intraday market. Nevertheless, later research (e.g., Liu and Qiao, 2017; Miao et al., 2017) employing alternative approaches and longer observation windows report stronger futures leadership.

A notable feature of the Chinese market is the asymmetry in trading mechanisms: on one hand, the mechanism of the spot market is T+1 trading, whereas that of the futures market allows T+0 intraday trading. This structural distinction might increase futures market's data digestion capabilities. Despite that, regulatory interventions — in particular a 2015 clampdown on index futures trading — vastly limited participation. Miao et al. (2017) acknowledge these limitations, but stop short of dynamically testing their impact. Therefore, how these policies influence price discovery remains mostly unexplored.

2.5 Gaps in the Literature and Research Motivation

However, despite extensive work on capturing price discovery, there are still some important gaps, especially about the index futures market in China. First, relatively few studies focus on measurement of both long-term and short-term information transmission based on high-frequency intraday data. Most existing studies are limited to daily or 5-minute data over narrow time spans. Second, the effects of policy interventions, the most recent being the 2015 regulatory shock, have not been empirically modeled in a time-varying or regime-switching framework. Finally, some studies may suffer from sample selection bias by focusing only on the first post-launch years of the CSI 300 futures contract and having omitted that what happened subsequently on the market, when the CSI 300 futures could recover post-2018.

In light of these limitations, this study aims to provide a more comprehensive and updated analysis of the price discovery process between CSI 300 index futures and the spot market using five-minute high-frequency data for the year 2024. By employing vector error correction models, Granger causality tests, and Information Share methodology, the study investigates both the long-run equilibrium and short-term dynamics between the two markets. It also intends to explore to what extent the futures market reclaimed the lead in price discovery in the wake of the 2015 regulatory shock in China after returning to a fast-developing and mature market, thereby informing China's market development maturity and information efficiency.

3. Data Description

We collected data on the prices of the CSI 300 index futures and its corresponding spot index on a 5-minute basis, totalling 10845 observations. The observations span the entire regular trading hours of every trading day in 2024, from January 2 to December 31, 2024. Due to the nature of trading, each day starts with a jump that reflects overnight price changes. The first return of every day is omitted to avoid potential bias in return-centric analyses.

Table 1 presents the summary statistics for the log returns of the futures and spot series. As expected, the average return and return volatility for both markets remains near zero. The mean return is slightly higher for the futures market as compared to the spot market, a disparity which remains insignificant from an economic perspective. When looking at volatility, the sample standard deviation of returns is slightly higher for futures, suggesting an increasing responsiveness to incoming information. Additionally, both return series demonstrated some weak positive skewness alongside moderate excess kurtosis, suggesting the presence of moderate jumps in returns.

To examine how closely the two markets move together, we calculated the Pearson correlation coefficient between the 5-minute futures and spot prices. The result presented in Table 2 indicates a strong positive correlation of 0.9986, which establishes that the two price series are nearly synchronized within a single trading day. This strong correlation justifies the further examination of the hypothesis that one market may dominate the other in the use of information.

Figure 1 displays the 5-minute price series of the futures and spot indices for the sample period. The two series almost replicate their movements over time which indicates a very strong relationship. We will formally examine this relationship using cointegration techniques in the next section

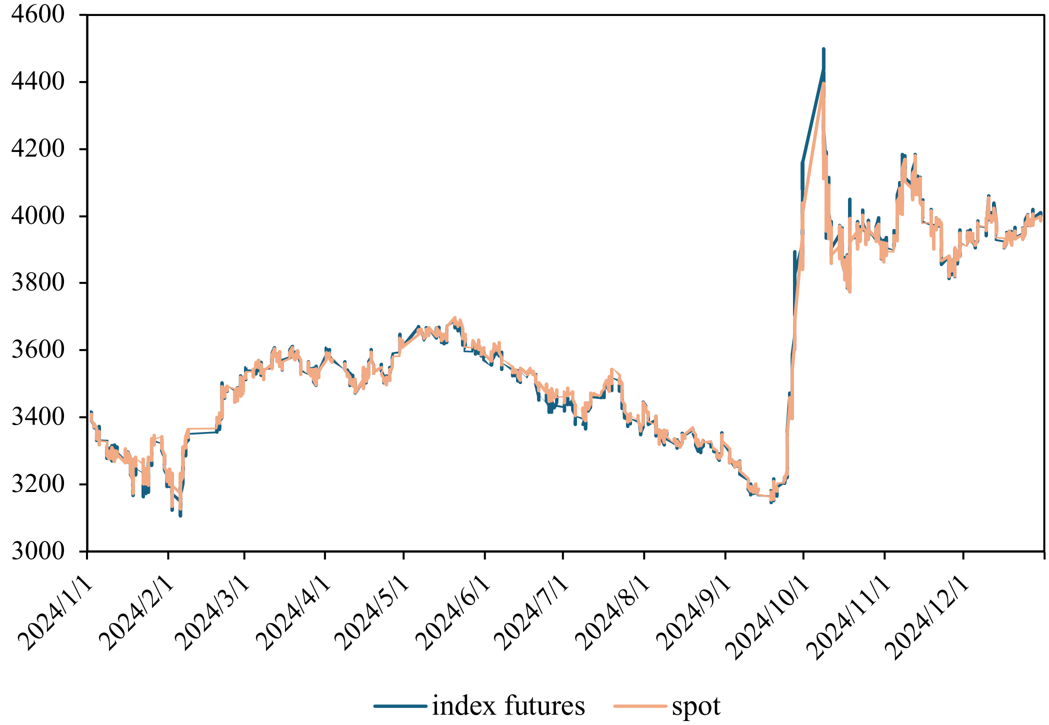
Table 1: Summary Statistics for 5-Minute CSI 300 Index Futures and Spot Returns

	Index Futures	Spot
Observations	10845	10845
mean	0.000007	0.000012
std	0.001724	0.001553
min	-0.024175	-0.016993
25%	-0.000703	-0.000690
50%	-0.000049	-0.000023
75%	0.000670	0.000677
max	0.033054	0.032084
skewness	1.034473	1.314286
kurtosis	36.934835	36.044552

Table 2: Correlation Matrix Between CSI 300 Index Futures and Spot Prices

	Index Futures	Spot
Index Futures	1.0000	0.9986
Spot	0.9986	1.0000

Figure 1: 5-Minute Price Movements of CSI 300 Index Futures and Spot



4. Methodology

Using high-frequency data, this study uses a multi-step econometric approach to analyze the directional relationship between the CSI 300 index futures and spot markets, as well as the price discovery process. The analysis blends stationarity testing, cointegration analysis, Granger causality analysis, error correction modeling, and information share decomposition.

4.1 Stationarity Test: Augmented Dickey-Fuller (ADF)

To check for the validity of the model, we first perform the stationarity test for the log futures and log spot prices series by the ADF test. The test equation is given by:

$$\Delta y_t = a_0 + a_1 \cdot t + \gamma \cdot y_{t-1} + \Sigma_i\, c_i \cdot \Delta y_{t-i} + \varepsilon_t$$

where y_t is the log price, Δ denotes the first difference, and ε_t is a white-noise error term. The null hypothesis H_0: $\gamma = 0$ indicates a unit root (non-stationarity). The series are confirmed to be integrated of order one, I(1), which is a necessary condition for cointegration analysis.

4.2 Granger Causality Test

We conduct Granger causality tests to examine whether lagged values of one market statistically predict the other. Formally, we test:

H_0: Futures do not Granger-cause spot

H_0: Spot does not Granger-cause futures

The test is applied to the first-differenced series (returns), with significance determined by the F-statistic.

4.3 Cointegration Test: Johansen Procedure

Given both series are I(1), we apply the Johansen test to examine whether a long-run equilibrium relationship exists. The Johansen trace test is based on the following VECM framework:

$$\Delta P_t = \alpha \cdot \beta^t \cdot P_{t-1} + \Sigma_i \Gamma_i \cdot \Delta P_{t-i} + \varepsilon_t$$

where P_t is the vector of log prices, $\alpha \cdot \beta^t \cdot P_{t-1}$ represents the cointegration term, α captures adjustment speeds, and β is the cointegrating vector. The number of cointegrating relationships is determined by comparing the trace statistics to critical values.

4.4 Vector Error Correction Model (VECM)

Once cointegration is established, we subsequently estimate a VECM to examine both the long-run long and short run relationships. The VECM includes an error correction term (ECT), which measures the speed by which the markets adjust when there is a deviation from the long-term equilibrium:

$$\Delta P_t = \alpha \cdot \beta^t \cdot P_{t-1} + \text{short-run lags} + \varepsilon_t$$

A significant ECT coefficient in the spot return equation suggests that the spot market adjusts to the futures market and is not the leader in price discovery. The number of lags is chosen using the Akaike Information Criterion (AIC).

4.5 Information Share (IS) Model

Finally, we implement the Hasbrouck (1995) information share decomposition to measure the relative contribution of each market to the efficient price. Using the residual covariance matrix Σ_u from the VECM, and performing Cholesky factorization under two orderings, we compute upper and lower bounds for each market's information share. For a two-market system:

$$IS_j = \gamma_j^2 / (\gamma_1^2 + \gamma_2^2), \quad j \in \{\text{futures, spot}\}$$

where γ is derived from $C^t \cdot \beta\_\perp$, and C is the Cholesky decomposition of Σ_u. The midpoint of the IS interval is interpreted as the market's contribution to price discovery.

5. Empirical Results

5.1 Stationarity and Cointegration Tests

Before proceeding with cointegration and error correction modeling, we examine the time series properties of the log futures and log spot price series using the ADF test. Table 3 reports the ADF test statistics and p-values under both level and first-difference forms.

The null hypothesis of the ADF test is that the series contains a unit root, i.e., it is non-stationary. It can be seen from the table that the log futures and log spot prices do not reject the null at levels, with test statistics of -1.3675 and -1.2860, and p-values of 0.5978 and 0.6356, respectively. This confirms that both series are non-stationary in levels.

After differencing once, the ADF statistics become -15.6357 for futures and -15.0795 for spot, with p-values both virtually zero. These results significantly reject the null hypothesis of a unit root at the 1% level, indicating that both series are stationary in first differences. Thus we conclude that both log futures and log spot price series are integrated of order one, I(1), which is a necessary condition for Johansen cointegration tests.

Table 3: Augmented Dickey-Fuller (ADF) Test

	At level		First difference	
	ADF Statistic	p-value	ADF Statistic	p-value
Futures	-1.3675	0.5978	-15.6357	0.0000
Spot	-1.2860	0.6356	-15.0795	0.0000

To further examine the short-run directional relationship between the CSI 300 index futures and spot markets, we conduct the Granger causality test using first-differenced log prices. The test then evaluates whether lags of one market provide significantly better forecasts of the other. Table 4 reports the F-statistics and p-values from the bivariate Granger causality test.

The findings imply an evident information asymmetry from one market to another. In particular, the null hypothesis that futures do not Granger-cause spot is strongly rejected, with an F-statistic of 470.0910 and a p-value of 0.0000. Conversely, the null that spot does not Granger-cause futures is also rejected, though with a much smaller F-statistic of 13.8645 and a p-value of 1.53×10^{-46}. These results indicate that there is a bidirectional causality in both markets and the size of the causal effect from futures to spot is much higher.

This result provides initial evidence that the futures market tends to incorporate information more rapidly, which is consistent with the typical role of futures in leading price discovery. We then move on to cointegration analysis to test if this short-term dominance between the two is predicatively translated into a long-run equilibrium relationship.

Table 4: Granger Causality Test

	F-statistic	p-value
Futures → Spot	470.0910	0
Spot → Futures	13.8645	1.53E-46

To assess whether the CSI 300 futures and spot prices share a long-run equilibrium relationship, we apply the Johansen cointegration test on the log-level price series. The test is based on a vector error correction framework that allows for the estimation of multiple cointegrating vectors. Both the trace statistic and maximum eigenvalue statistic are employed under a constant intercept and no deterministic trend specification.

The optimal lag length of 20 is selected based on the AIC. Given the 5-minute sampling frequency, such a relatively high lag order is appropriate for modeling the fast-paced dynamics between the two markets.

The test results are reported in Table 5. The value of the test statistic for the null hypothesis of no cointegration is 71.3053 for the trace statistic and 69.3675 for the maximum eigenvalue test, greater than the respective 95% critical value of 15.4943 or 14.2639 at 5%. This strongly rejects the null hypothesis at the 1% level. For the null of at most one cointegrating vector ($r \leq 1$), both the statistics are less than the critical value (3.8415) revealing that strictly one cointegrating relationship does exist. This result indicates that although the futures price and the spot price are individually non-stationary, they are cointegrated, and therefore exhibit a stationary long-run equilibrium relationship. This finding indicates why a VECM model is suitable in the following sections as used to jointly analyze short-run dynamics and long-term adjustment behavior between the two markets.

Table 5: Johansen Cointegration Test

Null Hypothesis	Trace Statistic	0.05 Critical Value	p-value	Max-Eigen Statistic	0.05 Critical Value	p-value
r = 0	71.3053	15.4943	0.0000	69.3675	14.2639	0.0000
r ≤ 1	1.9377	3.8415	0.1149	1.9377	3.8415	0.1149

5.2 Vector Error Correction Model (VECM)

After confirming the existence of cointegration in the long run between the futures and spot prices of the CSI 300 index, we estimate a VECM which can account for both long run equilibrium and short run dynamics. The VECM contains an error correction term (ECT), obtained from the estimated cointegrating vector, which captures short-run deviations from long-run equilibrium.

Table 6 shows the VECM estimation results. The coefficient of the ECT in the spot return equation is statistically significant and negative ($\alpha = -0.00433$, $t = -20.4033$), indicating that the spot market actively adjusts to restore long-run equilibrium when deviations occur. In contrast, the ECT coefficient in the futures return equation is small and statistically insignificant ($\alpha = -0.0057$, $t = -0.9297$), suggesting that the futures market does not significantly respond to long-run disequilibrium.

These results suggest a clear direction of adjustment: the futures market leads the price discovery process, and the spot market adjusts passively to absorb information reflected in futures prices. This is also consistent with the results in Table 2 on Granger causality test and supports the theoretical role of futures markets as more efficient information processors.

Table 6 Vector Error Correction Estimates

Cointegrating Eq:	CointEq1	
LOG_FUTURES(-1)	1	
LOG_SPOT(-1)	-1.020981	
	-0.00272	
	[-375.134]	
C	0.172469	
	-0.02226	
	[7.74689]	
Error Correction:	**D(LOG_FUTURES)**	**D(LOG_SPOT)**
COINTEQ1	0.023449	0.072356
	-0.0057	-0.00433
	[4.11034]	[16.7199]
D(LOG_FUTURES(-1))	-0.058378	0.638346
	-0.01165	-0.00884
	[-5.01148]	[72.2396]
D(LOG_FUTURES(-2))	0.001986	0.277571
	-0.01331	-0.0101
	[0.14920]	[27.4844]
D(LOG_SPOT(-1))	0.012541	-0.377713
	-0.01334	-0.01012
	[0.93978]	[-37.3128]
D(LOG_SPOT(-2))	-9.64E-03	-1.61E-01
	-1.04E-02	-7.87E-03
	[-0.92973]	[-20.4033]

In addition to the long-run error correction mechanism, the short-run lag coefficients in the VECM also reveal directional influence. Specifically, the lagged spot returns have significant impact on futures returns, while the effect of lagged futures returns on spot is much weaker and less robust. Thus, the futures market becomes paramount for the short run price discovery process.

Taken together, the VECM estimation provides robust evidence that the CSI 300 index futures market plays a predominant role incorporating new information, and the spot market adjusts accordingly to maintain a long-run equilibrium.

5.3 Price Discovery Measures

To quantify the relative contribution of the futures and spot markets to the efficient price, we employ the information share (IS) methodology. This approach uses the residual covariance matrix from the VECM estimation to decompose the variance of innovations to the common efficient price into market-specific components. Since the IS measure is sensitive to the Cholesky ordering of variables, we compute upper and lower bounds for each market by alternately placing the futures and spot markets first in the ordering.

The IS estimates, based on the VECM residual covariance matrix using log price series (5-minute frequency, lag 2, downsampled every 30 observations), are presented in Table 7. The results show that the information share of the CSI 300 index futures ranges from 0.9805 to 0.9829. In contrast, the spot market's information share lies between 0.0171 and 0.0195.

These findings indicate that the futures market overwhelmingly dominates price discovery. Even under the most conservative ordering assumptions, the futures market still accounts for at least 98.05% of the common price innovations. This result is consistent with the previous Granger causality and VECM evidence and highlights the futures market's superior role in incorporating new information.

Table 7: Information Share Model Results

	Futures	Spot
Lower Bound:	0.9805	0.0171
Upper Bound:	0.9829	0.0195

6. Conclusion

This paper investigates the price discovery dynamics between the CSI 300 index futures and the underlying spot index using high-frequency data. Leveraging one year of 5-minute log price observations, we apply comprehensive econometric tools including unit root testing, Johansen cointegration analysis, VECM, Granger causality testing, and Information Share model.

The empirical results indicate that the CSI 300 index futures and spot series are I(1) process and exhibits long-run cointegration relationship, indicating that the use of VECM approach is appropriate. The estimation of VECM shows that the spot market has a significant ECT while the futures market does not. This suggests that the spot market does adjust substantially to move the process back toward the long-run equilibrium, while the futures market does not respond strongly to deviations—confirming the idea that the futures market picks up new information quickly.

The Granger causality test further supports this conclusion and exhibit a powerful one-way causal predictability from futures to spot returns. This suggests that the future market are also leading the price discovery in the short run.

We utilize the Hasbrouck Information Share (IS) to measure the extent to which each market contributes to the efficient price. The findings reveal that the CSI 300 index futures contribute for more than 98% on the most common efficient price innovations, even with the most conservative Cholesky ordering. The spot market had very marginal contribution of less than 2%, which indicates that it plays a more passive role in price discovery process.

Together, these results provide robust evidence that the CSI 300 index futures market dominates the price discovery process in the Chinese equity market. This dominance is likely due to the greater responsiveness, liquidity, and institutional involvement in the futures market.

These results have practical implications for investors and regulators. Investors can take from his results that the futures market can indeed be a trustworthy gauge of the market's expectations. For regulators, a knowledge of the mechanisms of price discovery can help in the formulation of more efficient and transparent market structures.

Future research could extend this analysis by incorporating time-varying measures of price discovery, testing alternative market regimes, or examining the role of macroeconomic news and investor sentiment in driving lead-lag relationships. Moreover, more detailed analysis with other major index futures products, such as CSI 500 and SSE 50 in China, could provide a deeper understanding of the price discovery mechanisms in different markets.

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