The Economics of CSI300 Stock Index Futures in China

ZHOU, SHANGCHEN

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By

Zhou Shangchen

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Durham University Business School

University of Durham

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Abstract

Chinese financial markets play an ever more pertinent role within the global economic. In this thesis, we investigate empirically the efficiency and functioning of the Chinese Security Index 300 (CSI300) index future. While CSI300 index futures market is a relatively new market, it has attracted huge trading volume and liquidity as there is no other financial derivatives markets in China and the short-selling in the stock market is difficult. Therefore, it is important and informative to examine both the hedging effectiveness and price discovery ability of CSI300 stock index futures.

This thesis presents one of the first attempts in empirically investigate the market efficiency and hedging effective of the Chinese stock index futures from 2012 to 2018. In particular, chapter 2 studies the hedging effectiveness of CSI300 index futures with both static and dynamic hedging methods. The results show that CSI300 stock index futures is an effective hedging instrument, and in general the performance of dynamic models are better than static models. In chapter 3, we analyze the price discovery contribution of CSI300 index futures market in the context of six relevant hypothesis and three empirical measures (PT/GG, IS, and MIS methods). The price discovery performance of Chinese stock index futures is found to be consistent with the other mature markets, indicating that new information that affects the fundamental value is reflected more quickly in the CSI300 index futures markets. Finally, using the efficient market hypothesis and unbiasedness hypothesis, CSI300 index futures is also found to be informational efficient in chapter 4. The market is partially efficient and

the futures price is a constant risk unbiased predictor for the subsequent spot price in the long run.

Different from previous literature which focus on the CSI300 futures and spot market, this thesis utilizes various data frequency and futures with different maturity to address the empirical issues regarding the functioning of CSI300 futures market. In addition, this thesis is the first study to the impact of regulation reforms in 2015 (when Chinese regulators strictly tightened the rules on trading stock index futures) on CSI300 index futures market. Finally, the performance of the CSI300 index futures market has been compared and evaluated with other more mature index futures markets around the globe. The findings of this thesis have important implications to market regulators and participants in developing more effective investment and regulatory strategies.

Declaration

The material contained in this thesis has not been submitted in support of an application for another degree or qualification in this or any other University.

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Chapter 1 - Introduction

1.1 Research Background

The question of the impact of stock index futures on underlying market volatility has long been of interest to both researchers and regulators. While financial theory suggests that futures markets facilitate hedging, a more popular perception is that they serve as a means of speculation, and that higher price volatility tends to invite more speculation. This perception has resulted in many legislative attempts[1], which have been largely unsuccessful to reduce the amount of trading in futures markets. (Eric and Ray, 2000)

The information-based hypothesis argues that prices are determined by the interaction between hedgers and informed speculators (Gulen and Mayhew 2000). It is likely that in countries with highly developed financial institutions, futures introduction offers only modest risk-sharing benefits while introducing a large number of speculators with noisy information. In other countries, the introduction of futures may have greater risk-sharing benefits that counteract the "informational externality" associated with partially informed speculators.

The world's first stock index futures contract was the Value Line contract, introduced by the Kansas City Board of Trade on February 24, 1982. Today, stock index futures and options trade in markets all over the world, with new contracts launched nearly every year. Table 1.1 reports launch dates for thirty nations that

[1] In the history of the United States, over 100 bills have been introduced to curtail, or even abolish altogether, trading in futures markets. In almost every case, however, the measure has failed to pass. One exception occurred in 1958, when Congress passed a bill prohibiting futures trading in onions, which was then an active market. See Teweles, Harlow, and Stone (1974) for details.

introduced stock index futures between 1982 and 2014.

Table 1.1 Launch Dates for Index Futures Contracts

Country	*Underlying Index*	*Launch Date*
United States	Value Line	24 February 1982
(CME)	S&P 500	21 April 1982
Australia	All Ordinaries	16 February 1983
United Kingdom	FTSE 100	3 May 1984
Canada	TSE 300	16 January 1984
Brazil	BOVESPA	14 February 1986
Hong Kong	Hang Seng	6 May 1986
Japan (SIMEX)	Nikkei 225	3 September 1986
(Tokyo)	Topix	3 September 1988
New Zealand	Barclay Share	January 1987
Sweden	OMX	3 April 1987
Finland	FOX	2 May 1988
Netherlands	AEX	24 October 1988
France	CAC 40	9 November 1988
Denmark	KFX	7 December 1989
South Africa	All Share	30 April 1990
Switzerland	SMI	9 November 1990
Germany	DAX	23 November 1990
Chile	IPSA	December 1990
Thailand	SET50	1 January, 1991
Spain	IBEX 35	14 January 1992
Austria	ATX	7 August 1992
Norway	OBX	4 September 1992
India	SEX30	November 1992
Belgium	BEL 20	29 October 1993
Italy	MIB 30	28 November 1994
Hungary	BSI	31 March 1995
Israel	Maof 25	27 October 1995
Malaysia	KLCI	15 December 1995
Korea	KOSPI 200	3 May 1996
Portugal	PSI-20	20 June 1996
Russia	RTS	March 1997
Venezuela	IBC	5 September 1997
Poland	WIG20	16 January 1998

Greece	FTSE/ASE-20	27 August 1999
Indonesia	ISE30	July 2007
China	CSI300	24 April 2010
Turkey	BIST30	November 2014

The list of underlying index and launch date for different countries. NOTE: Initial trading dates for various Index Futures contracts. Sources: Gulen et al. (2000), and information published by the individual exchanges, and Futures Industry Association Fact Book.

Different countries have different contract designs, trading mechanisms, and regulatory environments. Some countries (e.g. United States, Japan, Korea and India) have listed index options in addition to index futures, and others have not. Some countries have competing offshore contracts, like SIMEX in Singapore launched 6 offshore index futures contracts, but others do not. Moreover, the events in table1.1 are clustered in time, with a group of English-speaking developed countries listing in the early 1980s, a group of Western European and other developed markets listing in the late 1980s, and emerging markets listing in the 1990s. Bessembinder and Seguin (1992) finds that country-specific conditional variance is more likely to decline than to increase with the introduction of stock index futures. They document that the markets in most countries are significantly more integrated with the world market after the introduction of stock index futures.

Price discovery is the process by which new information is incorporated into asset prices. Given two closely related markets, the market with faster information processing would be expected to play the dominant role in price discovery. A stock index futures market and its underlying stock index market are a classic example of two closely related markets. A large body of research has found evidence that stock index futures markets (due to lower transaction costs and the lack of short-sale restrictions) respond to the arrival of new information faster than the corresponding cash market index and lead changes in its associated stock index in the United States (Chan, 1992; Chou & Chung, 2006; Hasbrouck, 2003; Kawaller, Koch, & Koch, 1987; Stoll & Whaley, 1990), the United Kingdom (Abhyankar, 1995; Tse, 1999), Japan (Iihara, Kato, & Tokunaga, 1996), Germany (Booth, So, & Tse, 1999; Gaul & Theissen, 2008) and Hong Kong (So & Tse, 2004). Covrig, Ding, and Low (2004) show that even domestic stock index futures traded on a foreign market can play a significant price discovery role for the domestic stock index. After reviewing the existing evidence, Gulen and Mayhew (2000) found little reason to expect that the introduction of new stock index futures contracts in emerging nations will destabilize stock markets. On the contrary, in nearly every country outside of the US and Japan, it appears that futures markets have had either no significant effect or else have been associated with a significant decline in volatility and increased integration with the world market[2].

Prior to our main empirical analysis and discussion, it is worth providing an overview of the stock and index futures markets in China to clarify the concepts introduced later. In Mainland China, there are two stock markets, the Shanghai Stock Exchange, which launched in 1990, and the Shenzhen Stock Exchange, which launched in 1991. The two stock exchanges each have separate markets for different

[2] Examining the dummy coefficients in the conditional covariance equations, the conditional covariance with the world market increases in 21 out of 25 countries, with statistical significance in 13 cases. It may be interpreted as evidence that futures markets contribute to an increase in the level of world-market integration. Gulen and Mayhew (2000)

share classes called A and B shares. The key distinction between the two is that A shares are denominated in Chinese currency (CNY), whereas B shares are denominated in foreign currency (USD in Shanghai and HKD in Shenzhen). Another main difference is that the A-share market was closed to foreign investors, whereas the B-share market was open to only foreigners. However, the B-share market was opened to Chinese investors in 2001, and select foreign institutions were allowed to buy A shares in 2003. Some companies have their stocks listed on both markets, but in general, their B shares trade at a large discount compared to A shares, and the trading volume of B shares is much smaller than that of A shares.

On April 8, 2005, the China Securities Index Company Ltd created the Chinese Securities Index 300 (CSI 300), the first broadly based stock market index. The CSI 300 Index is a value weighted stock market index comprising 300 large-capitalization and actively traded A-share stocks listed on the Shanghai or Shenzhen Stock Exchange; it is reconstituted every 6 months. The CSI 300 Index constituent stocks represent approximately 60% of the total market capitalization in both exchanges, and investors generally agree that it reflects the overall performance of the entire A-share markets in China.

The China Financial Futures Exchange (CFFEX) launched the country's first stock index futures, the CSI 300 index futures, on April 16, 2010. The underlying asset is the CSI 300 Index, which consists of 300 listed stocks with the largest market capitalization and active trading on the Shanghai and Shenzhen Stock Exchanges. After 9 years of development, the CSI 300 index futures have become one of the most actively traded financial instruments of the Chinese financial markets. As in peak year 2015, the daily money volume of the index futures was CNY 1687 billion (approximately USD 260 billion), according to the CFFEX report (2015).

Table 1.2 CSI300 Stock Index Futures Contract Table

Underlying Bond	CSI 300 Index
Contract Multiplier	CNY 300
Unit	Index point
Tick Size	0.2 point
Contract Months	Monthly: current month, next month, next two calendar quarters (four total)
Trading Hours	09:30 am - 11:30 am, 01:00 pm - 03:00 pm
Limit Up/Down	±10% of the settlement price on the previous trading day
Minimum Margin Requirement	8% of the contract value
Last Trading Day	Third Friday of the contract month, postponed to the next business day if it falls on a public holiday
Delivery Day	Third Friday, same as "Last Trading Day"
Settlement Method	Cash Settlement
Transaction Code	IF
Exchange	China Financial Futures Exchange

The detail index information for CSI300 stock index including underlying bond, contract multiplier, unit and so on. From CFFEX

http://www.cffex.com.cn/en_new/CSI300IndexFutures.html

In the index futures market, four contracts with different expiration days are usually being traded simultaneously. The four expiration days are the third Fridays of the current month, the next month, and the subsequent two quarter-ending months. Quarter-ending months refer to March, June, September, and December. For example, the four contracts traded in early January expire on the third Fridays of January, February, March, and June. The expiration days of the futures traded in early February are the third Fridays of February, March, June, and September. The futures contract is quoted in index points but the contract size is the index point multiplied by CNY 300. One notable feature in the index futures market is that its trading hours are 30 minutes longer than those of the underlying stock markets. The stock markets open at 9:30 and close at 15:00, whereas the index futures market opens 15 minutes earlier and closes 15 minutes later.

Figure 1.1 CSI300 Index Futures Price and Volume (2010.4-2019.12)

The bar graphs of weekly trading price (upper panel) and volumes (bottom panel) of CSI300 Index Futures from 2011/01 to 201. The lines in the upper panel represent for mean average with different looking back and the extreme values are marked with numbers in red (local maximum) and green (local minimum), respectively. Source. The figure is taken from CFFEX http://www.cffex.com.cn/hs300/

To avoid excessive speculation, the CFFEX has imposed restriction rules on the index futures market participants. An eligible investor trading on the CSI 300 index futures must satisfy the following three requirements. First, an eligible investor must have available funds of more than RMB 500,000 (80,050 USD). Second, they need to pass the relevant test to ensure she/he has basic trading knowledge of the index futures. Third, they must have transaction records of stock index futures simulation trading or commodity futures trading.

1.2 Research Aim and Objective

Chinese financial markets play an ever more pertinent role within the global economic context (Peck, Park, & Rozelle, 1998; Wang & Ke, 2005; Webb, 2016). Following the global financial crisis of 2008, economic stabilization has become a major concern for governments (Bergman & Hutchison, 2015; Lambert, Noth & Schüwer, 2015). One prominent source of potential instability, which has been a major target for stabilization efforts—especially in the case of China—is that of financial markets (Hanley, Kumar & Seguin, 1993; Tagkalakis, 2011).

In this study, we investigate the impact and functioning of stocks index futures trading using the introduction of Chinese Security Index 300 (CSI300) index future as a natural experiment. We choose the stocks index futures in China rather than in developed countries for three main reasons: First, in developed markets the coexistence of various financial derivatives (e.g., single stock futures, options, and credit default swaps [CDSs]) increases the difficulty of isolating the impact of stocks index futures on spot price, whereas the CSI300 index futures is the only financial derivative in Chinese financial markets during our sample period.

Second, short selling is very difficult in Chinese stocks market. Before March 31 2010, no methods for investors to short stocks. After that, the securities broker was allowed to loan stocks from clients[3]. (SEC 2010) However, due to the limited pools, loaning is very difficult in actual transactions. The lack of stocks mitigates the impact of short sellers on capitalizing negative information into stock prices and thus provides an ideal environment to examine the influence of stocks index futures' short flexibility.

Third, since the CSI300 index future is one of the most liquid equity index futures in the world, total of 217 million CSI300 index future contracts were traded, ranking fifth in global stock index futures in 2014[4] and the trading volume increased 54.5% (to 335 million contracts) in 2015[5]. For many other emerging markets, illiquidity may potentially lead to inconclusive conclusions from empirical investigations. The empirical research on the Chinese market, however, does not have a significant illiquidity issue.

1.2.1 Hedging Effectiveness

Hedging is commonly understood to be undertaken to reduce the risk of holding a portfolio of risky assets. This has not always been the sole interpretation of hedging. The founder of modern derivatives research, Working (1953), considered hedging as

[3] Securities Company Margin and Loan Management Measures, launched on March 31, 2010

[4] http://www.cffex.com.cn/sj/yearlymarketReport/2014/2014YearlyMarketReport.pdf

[5] http://www.cffex.com.cn/sj/yearlymarketReport/2015/2015YearlyMarketReport.pdf

speculating upon changes in the relationship between spot and futures prices. Today's understanding and interpretation of hedging is based on the seminal papers by Johnson (1960) and Ederington (1979), where the objective of hedging was to minimize hedged portfolio variance. The Johnson/Ederington methodology specified an optimal hedge ratio (OHR) as the proportion of short futures contracts held for each long portfolio position, maximizing the risk-averse agent's expected utility. In a mean-variance framework, and a one-period setting, the optimal hedge ratio minimized the total variance of the hedged portfolio return and could be obtained from an OLS regression of unhedged portfolio returns on futures returns. The optimal hedge ratio therefore became known as the minimum-variance hedge ratio (MVHR).

Practitioners long realized that this hedge ratio should not be a static measure, but should instead be updated inter-temporally. This need for dynamic hedging evolved from a recognition of time variation in the joint distribution of spot and futures returns. In the late 1970s and early 1980s—now known as the pre-ARCH model era—several academics modeled the benefits of dynamic hedging schemes. Early academic versions of dynamic hedging (see, e.g., Breeden, 1984; Ho, 1984; and Stulz, 1984) exploited the notion that only recent history contained relevant information for the optimal hedge ratio by inter-temporally updating the information set. This became subsequently known as the rolling-window methodology.

In the late 1980s, the post-ARCH model era, it became clear that there is a need for dynamic hedging as the (co-)variance of spot and futures returns is time dependent. Hedging models that accounted for time-varying covariance have invariably been based on ARCH (Engle, 1982), or GARCH specifications (Bollerslev, 1986). Many studies reported significantly reduced hedged portfolio variance, at least for short hedging horizons, with time-varying methodology (Baillie & Myers, 1991; Cecchetti, Cumby, & Figlewski, 1988). Critics argued that the benefits of too-frequent rebalancing would soon be offset by transaction costs. Kroner and Sultan (1993), however, showed that even after accounting for transaction costs, there was still a significant out-of-sample advantage for GARCH-based time-varying currency hedging. Sim and Zurbruegg (2001), on the other hand, illustrated that GARCH-driven changes in stock-index futures hedge ratio were too frequent/large and could therefore incur prohibitive transaction costs. Simpler and less frequently updated dynamic hedging strategies, like the rolling-window hedge, could then still be preferable. This is because the optimal hedge ratio is determined by the ratio of the conditional covariance of spot and futures returns to the conditional variance of futures returns (Kroner & Sultan, 1993).

Several studies have used multivariate generalized autoregressive conditional heteroskedasticity (GARCH) models for the modeling of returns, forming so-called GARCH hedging strategies (Baillie & Myers, 1991; Brooks, Henry, & Persand, 2002; Cecchetti, Cumby, & Figlewski, 1988; Kroner & Sultan, 1993; Lien, Tse, & Tsui, 2002). Although these GARCH models capture the time-varying covariance structure of spot and futures returns, recent studies have documented that a GARCH hedging strategy incorporating realized measures computed from high-frequency data (e.g., popular realized covariance) results in a better hedging performance than the conventional GARCH strategy (Lai, 2016; Lai & Sheu, 2010).

In this thesis, hedging effectiveness of CSI300 index futures will be examined with static and dynamic hedging methods. Although a number of studies has aim to identifying the minimum-variance hedge ratio (MVHR) using static and dynamic methods, there is no consensus on which method would be the best to calculate the optimal hedging ratio. Nonetheless, the CSI300 index futures have been launched nearly 10 years in the Chinese futures market, the question of which methods should be used to undertake effective hedging operations is an important issue worthy of additional attention. Li (2010) used OLS, VAR, ECM, and BEKK to study the hedge ratio of CSI300 index futures simulation transaction data. The results show that the dynamic hedging is better than the static hedging model in the sample, but the effect outside the sample is different. In chapter 2, based on various frequency, different contracts, and regulatory reforms on CSI 300 index futures, we examine the hedging performance of both the constant and time-varying hedge ratios by employing variance reduction as the performance benchmark. The extant literature has pointed out that, compared with stock index futures contracts in other mature markets, the price discovery ability of CSI 300 index futures is weak and the risk hedging effectiveness (HE) is relatively lower (Wei, 2013). Fu and Zhang (2010) indicate the next month contract of the CSI 300 index futures has better intraday risk hedging effectiveness than the current month contract, contradicting traditional hedging theory. Moreover, the policy impacts on the hedging effectiveness is also discussed. Since the basic statistic components (e.g., liquidity, trading volume, transaction cost, validation, etc.) are changed simultaneously after the implantation of policy, the effects are packaged to one parameter instead of discussing the relationship between single component and hedging effectiveness.

The main findings of chapter 2 can be summarized as follows. First, based on the daily hedging performance, the CSI300 index futures hedging effectiveness (HE) of static and dynamic models is between 73% and 85%, indicating that CSI300 index futures has the potential for investors to hedge the underlying market risks. Second, for the first time, we examine the hedging effectiveness of CSI300 index futures before and after regulation reforms in 2015. Almost all of models show the hedging effectiveness of CSI300 index futures drop significantly after the regulatory reforms. The limiting participation in Chinese stock index futures in 2015 could directly lead to reduce the hedging effectiveness, and making the stock index futures lose its the main function as hedging instruments. Third, all CSI300 index futures contracts with maturity terms show that the dynamic model has a superior hedging effectiveness. The best hedging effectiveness is the daily data, and the performance of dynamic models (Average HE = 83%) are better than static models (Average HE = 76%). They show that dynamic hedge ratios outperform constant hedge ratios in terms of reducing the portfolio risk, and dynamic hedging (hedge ratios are updated with the arrival of new information into the market) significantly improves the effectiveness. The static OLS (HE=74.32% in daily data) and VECM models (HE=77.42% in daily data) did not show significant differences in terms of hedging ratio and hedging effectiveness. Therefore, for CSI 300 stock index futures, a simple OLS model is a good choice if only static models are considered.

Fourth, as the contract expiration period get longer, the hedging ratio (MVHR) is gradually decreasing, and the hedging effectiveness is gradually reducing, which is in line with the implications of traditional theory. Finally, compared to the hedging effectiveness of 5-min and 60-min level data, the daily-level hedging is the most effective strategy, suggesting that CSI300 index futures is an effective tool for hedging.

1.2.2 Price Discovery

Price discovery, the process by which new information is impounded into prices, is probably the most important function of financial markets. As it is often the case that there are more than one market or trading venue where the same security or very similar securities can trade, or when both a security and its derivatives are traded, one of the long-standing key issues is how to estimate the contribution of each market to the price discovery process. The empirical finance literature has proposed and used a variety of methods for estimating price discovery contribution of each market.

The following extant literatures in analyzing the relationship between futures contracts and their underlying spot indices, report a lead-lag relationship of up to 30 minutes from futures prices to the spot price. This includes work by Stoll and Whaley (1990) on the S&P 500 and the Major Market Index; Chan (1992) and Koutmos and Tucker (1996) on the S&P 500; Iihara, Kato, and Tokunaga (1996) on the Nikkei

Stock Average; and Abhyankar (1995) on the FTSE100. The reasons for this lead-lag relationship includes the fact that futures markets tend to have less restrictive regulation and lower transaction costs than their stock market counterparts. Specifically, there tends to be increased liquidity and financial leverage due to fewer restrictions on short selling and marking to market trading. In addition, stock index futures contracts offer investors with an easy means to speculate and hedge market-wide trends.

In examining the price discovery process between spot, futures, and options prices Fleming, Ostdick, and Whaley (1996) observed that the market with the lowest trading costs tend to react more quickly to new information. This "trading cost hypothesis" can explain a number of results where stock prices tend to lag the futures market. More recently, studies have focused on the interplay between various futures markets. Examples include Craig, Dravid, and Richardson (1995) and Tse, Lee, and Booth (1996) who show that futures contracts listed in different international markets transmit and impound information from other exchanges efficiently. Kim, Szakmary, and Schwarz (1999) examine the role that trading costs have when examining price discovery across the S&P 500, NYSE, and MMI futures with their respective spot indices. Sim and Zurbreugg (1999) find evidence of cross-market linkages where Japanese Nikkei index futures partially relay information to the Australian All-Ords futures market.

As interest in the interrelationship between markets has grown, new techniques have also been developed to measure price leadership and dissemination across markets. For instance, Gonzalo and Granger (1995) and Hasbrouck (1995) provide measures that attempt to identify the price discovery process via the information share that each market holds relative to a common long-run factor. Capturing the information content revealed in one market explains the price leadership that exchanges have over others. Papers that have applied these techniques to futures studies include Booth, So, and Tse (1999) and Tse (1999a &b).

For the Chinese stock index futures market, most of the research focuses on the relationship between the CSI300 simulation futures market and the underlying CSI 300 index. For example, Yan. et al. (2009) used the vector error correction model, the common factor model, and the bivariate EGARCH model with error correction to study the CSI300 index from October 30, 2006 to March 20, 2009 using daily trading data. The price discovery and volatility spillover effects between the index futures market and the CSI300 spot market show that the spot market plays a leading role in price discovery, but there is no significant asymmetric two-way volatility spillover effect between the two markets. Xing and Zhang (2010) studied the linkage effect between CSI300 index simulation futures and CSI300 index, and found that the introduction of stock index futures did not have much impact on the volatility of the spot market, but increased the asymmetric effect in the underlying market. Nevertheless, during the simulation trading and real trading, the psychology of stock index futures and stock investors and their expectations will be greatly different, which will inevitably affect the price behavior of the simulation market and the real market.

Using the simulated transaction data instead of the real transaction data, the credibility and persuasiveness of the conclusions obtained are subjected to criticism. Since Chinese real stock index futures market has just recently been in operation, the empirical research on the information relationship between CSI300 index futures market and CSI300 spot market and the price discovery contribution is very limited. In chapter 3 of this thesis, using different frequency and different maturity contracts CSI300 data from 2012-2018, we aim to address this gap of literature by examining the price discovery role of CSI300 index futures markets. Taken together, we make the following contributions to the existing literature. First, this study adds to the extensive literature that investigates the information share of CSI300 stock index futures markets. Second, to the best of our knowledge, this is also the first attempt in investigating the price discovery of CSI300 futures market before and after the regulation reforms in 2015. Third, on the methodological front, we employ a number of testing methods to estimate the price discovery capability of CSI300 index futures and then compare it to that of other three major stock index futures markets on the S&P 500, Tokyo Stock Price Index (TOPIX), and Financial Times Stock Exchange (FTSE) 100, using daily price data. Finally, focus on the CSI300 index futures and spot market, chapter 3 utilizes both intraday (at 5min and 60min level) and daily data to examine the price discovery ability of CSI300 index futures in different frequency and contract maturity, in order to determine whether the market is microscopically effective. Overall, the results of chapter 3 on the price discovery role of CSI300 index futures should help market regulators and participants to develop more effective strategies.

Our empirical results show that the CSI300 index futures market contributes the majority of share of information, the spot market on the other hand does not seem to play a significant role in the information discovery process, indicating that CSI300 index futures market leads CSI300 underlying market. This is consistent with the findings of Lien (2009) who also found that price discovery takes place mostly in the futures market rather than in the spot market. Findings in this thesis suggest that the CSI300 index market and CSI300 index futures market are linked, and information will be transmitted from one market to another. Although regulatory reforms reduce the information share of CSI300 index futures, CSI300 index futures are still in the leading position. These results support the implications of trading cost hypothesis. The intraday transaction cost has increased significantly after the regulatory reforms, reducing the price discovery capability of CSI300 index futures intraday and affecting the price discovery function of CSI300 index futures. However, the transaction cost of futures remains much lower than that of the underlying market, CSI300 index futures market continue to lead the price discovery process in CSI300 spot market.

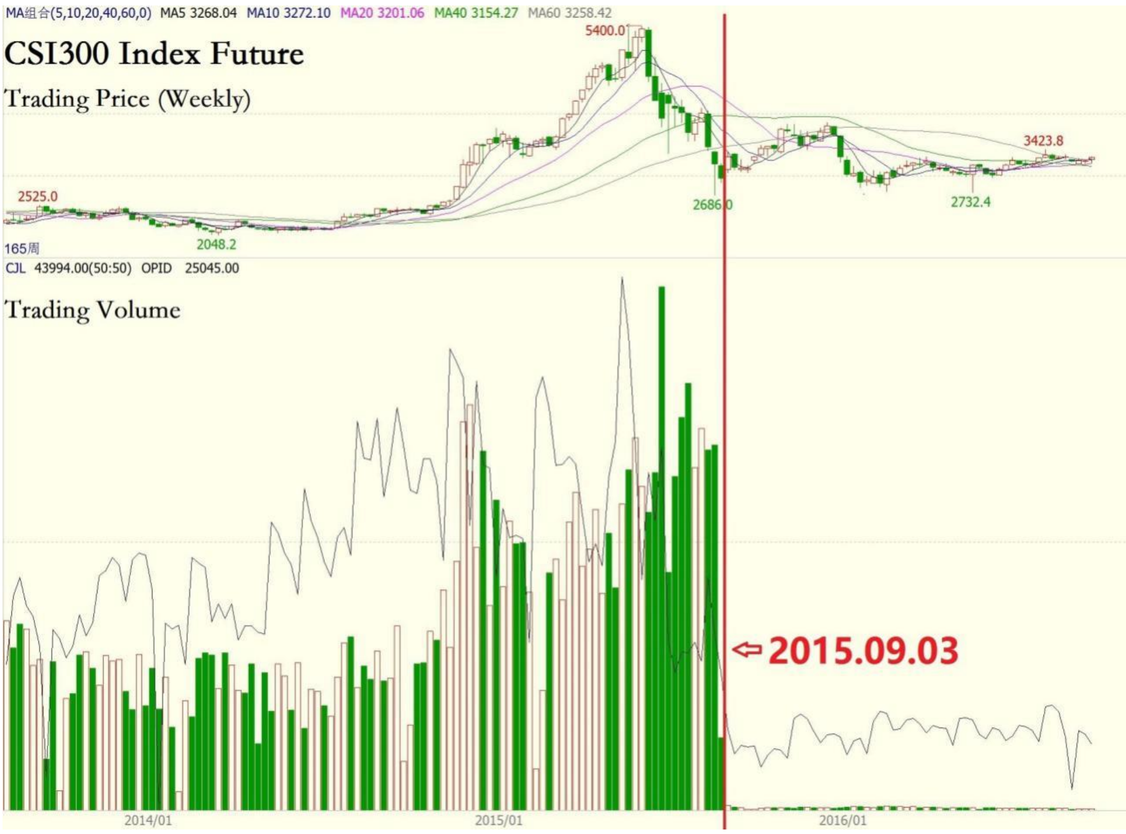
With regards to the maturity of contracts, the most current month contract of CSI300 index futures (IF1) always lead the next-month contracts (IF2) in information shares. CSI300 index futures market experiences an increase in the trading volume share of foreign and domestic institutional investors due to changes in regulation (Wei, 2018). According to Bohl and Salm (2011), institutional due to tighten of regulations, more institutional investors chose to trade in the next month contract. Switch between current month contract and next month contract can provide reference for investors' future trading behavior. Compared to other more mature markets (TOPIX, FTSE and S&P500), there is no significant difference in the role of CSI300 index futures and other index futures contracts. During the period between 2012 and 2018, the performance of CSI300 index futures is comparable to that of other mature markets as our information share measures indicated. This in turn suggests that in Chinese futures markets, new information that affects the fundamental value is reflected in the market rather quickly.

1.2.3 Impact of Regulatory Reforms

When the stock market is in turmoil, the derivatives markets will also be affected. As the volatility of the stock market and the volume of the derivatives trading increase, greater mispricing for the index options and futures arbitrage becomes more profitable. In addition, when the market is under stress (that is, demonstrated by extremely large upward or downward movements), investor behavior may become irrational and pricing errors may occur more frequently and persistently. (Cheng et.al 2000)

The Chinese stock market has taken a rollercoaster ride, as shown in Figure 1.2. From the beginning of 2015 until mid-June, the CSI 300 Index, which represents the broad Chinese A-share market, rose from 3500 to a high of 5178. Then it collapsed, losing over 34% in 20 days, with 1000 points erased in 1 week alone. On July 5, the Chinese government adopted a series of supportive measures, only to observe the market drop another 1000 points in the third week of August in 2015. Attempts were made to restrict program trading and to investigate abnormal individual trading accounts, but the efforts failed to restore the market stability. During this crisis, almost half of the listed stocks lost more than 50% of their pre-crash market value, and the largest loss was more than 77%. From mid-June to mid-September in 2015, on average, one in every four trading days witnessed more than 1000 stocks (approximately one third of the total number of stocks traded in the market) lose 10% of their value, that is, hit the lower bound of the daily price fluctuations. By any measure, this crash was among the most dramatic stock market crises in history.

Figure 1.2 CSI300 Trading Volume before and after Regulatory Reforms (2014-2017)



The weekly trading volumes (bottom panel) and price (upper panel) of CSI300 Index future from 2014-2017. The red perpendicular line represent for the boundary of regulatory reforms(2015.09.03) Source. The figure is taken from CFFEX http://www.cffex.com.cn/hs300/

Under heavy pressure from both market regulators and the general public, the CFFEX announced on August 25 that starting August 26, three measures would be adopted to curb speculative trading in the index futures market. First, the initial margin for non-hedging trades would be raised from 10% to 12%, 15% and finally 20% over the following 3 days. Second, any single day's total opening position greater than 600 contracts would be considered abnormal trade and be subject to increased scrutiny. Third, the clearing fees for intraday trades would be adjusted upward to 1.15 basis points. With the crisis developing further and the effect of government bailout measures quickly diminishing, September 2 witnessed the CFFEX announce yet another round of measures to curb speculative trade in the CSI300 index futures market. First, starting September 7, any single day non-hedging trading of over 10 contracts would be considered abnormal. Second, the initial margins for all non-hedging trading would be raised from 30% to 40%, and the initial margins for hedging trades would be raised from 10% to 20%. Third, the clearing fees for intra-day trades would be adjusted from 1.15 to 23 basis points. With these two rounds of strict measures, index futures trading in China nearly came to a complete stop, as shown in Table 1.3. This rare regulatory reform, which placed direct limits on the number of trades, provides us a unique setting to examine the functioning of index futures trading in an order-driven spot market. The speculative activity is also inhibited though the liquidity declines (Hu, et al, 2020; Chen & Gong, 2019), which enhances the influence of institutional investors, at least in some extent, especially for the larger ones.

In summary, under the intense social and economic pressure, the China Financial Futures Exchange (CFFEX) adopted a series of harsh restrictions on the scale of non-hedging open positions and effectively “terminated” index futures trading in China, such as increasing margin requirements and transaction fees as well as limiting the total volume of trade contracts, in late August 2015. Previous studies of these policies have focus on investigating primarily their direct impact on the Chinese stock market (Han & Liang, 2017). They find that the new trading policy adversely impacts stock market quality, a conclusion which has been found to be particularly valid for market liquidity.

We consider this rare event as a unique opportunity to re-examine the relationship between index futures trading and spot market quality because previous literature has mainly examined the issue by looking at the introduction, not the termination, of index futures trading. Han & Liang (2017) reject informed trader hypothesis and index-arbitrage theory, and propose a new explanation in light of the new trading restrictions. They argue that when futures trading is restricted, investors who have previously traded on alpha strategies (i.e., a long stock portfolio and short index futures) are exposed to systematic risk and will stop trading in spot market, deteriorating the market quality.

Table 1.3 Timeline of the major regulation changes in CSI300 index futures market

Announcement	Effective date	Contents
March 30, 2015	April 16, 2015	Transaction fee: 0.0025% & Filing fee: 0.01% of intraday closing transaction amount; Margin requirement: 10% of contract value
July 31, 2015	August 3, 2015	Transaction fee: 0.0023% of amount & Filing fee: CNY1 per transaction
August 25, 2015	August 26, 2015	Transaction fee: 0.0115% of amount & Filing fee: CNY1 per transaction Margin requirement: 12% of contract value for nonhedging position
	August 27, 2015	Margin requirement: 15% of contract value for nonhedging position
	August 28, 2015	Margin requirement: 20% of contract value for nonhedging position
August 28, 2015	August 31, 2015	Margin requirement: 30% of contract value for nonhedging position
September 2, 2015	September 7, 2015	Transaction fee: 0.23% of amount Filing fee: CNY1 per transaction Margin requirement: 40% (20%) of contract value for nonhedging (hedging) position Maximum limit on daily nonhedging opening trading: 10 contracts
December 7, 2015	January 1, 2016	Futures the extended trading of Index futures (9:15-9:30 and 15:00-15:15) are discontinued
February 16, 2017	February 17, 2017	Transaction fee: 0.092% of amount & Filing fee: CNY1 per transaction Maximum limit on daily nonhedging opening trading: 20 contracts Margin requirement: 20% of contract value for nonhedging position

The list of the major regulation changes and their corresponding announcement as well as effective date. Notes. Timeline of major regulation changes in the derivatives markets of CSI300.

In the Regulation of September 7, 2015 ‘Maximum limit on daily nonhedging opening trading: 10 contracts’ means: if the nonhedging open trades within a day is greater than 10 contracts in a single product, it is considered as “abnormal trading” and scrutinized by CFFEX. This strict limit has never happened in the history of Chinese stock index futures market.

Since the financial market crash in 2015, Chinese regulators and the public have cast serious doubts on the functioning of stock index futures market. The results of Han and Liang (2017) reveal that controlling for other variables, the effective termination of the CSI300 index futures trading has significantly reduced the index constituent stock market quality. As long as the index futures trading is not completely resumed, the resulting deterioration of spot market quality will continue to distort the market price and lead to capital misallocation. In addition, after the CFFEX trade restriction regulations, the trading volume of Singapore A50 index futures soared as international investors rushed to an alternative to hedge their risk exposure to the Chinese A-share market. On October 12, 2015, the Chicago Mercantile Exchange (CME) also launched its FT China 50 index futures. It is plausible that if Chinese regulators keep the door of index futures trading shut, then the CFFEX may lose ground to its overseas competitors.

In an efficient market, the futures prices can be interpreted as market forecasts of the subsequent spot prices at the maturity of those particular futures contracts. In order to analyze the impact of regulatory reforms on futures market, in chapter 4 of this thesis we empirically tests the two hypotheses on market efficiency and unbiasedness of the Chinese Securities Index futures (CSI300 index futures) to determine whether any long-run or short-run inefficiencies or pricing biases exist. The study also attempts to identify and estimate a risk premium. This chapter will use intraday data at 5-minute and 60-minute level in CSI300 stock index futures market to study for efficiency of Chinese stock index futures market from a perspective of weak form efficient market. Moreover, this chapter intends to compare the market efficiency before and after the regulatory changes in 2015. Overall, the results of chapter 4 should help market regulators in designing and formulating effective policies that contribute to index futures market's efficiency.

Our results indicate that, either before or after the regulatory changes, CSI300 index futures market is largely informational efficient. Using intraday data (5-min and 60-min level data) and daily data in different frequency, daily-level hedging effectiveness is the best, which also indicating that the CSI300 stock index futures are effective hedging instruments. And for the time period of 5-min, 60-min and daily level, the lower data frequency is, the performance becomes better. The overall result supports the idea that the market is partially efficient, and the futures price is not a zero-risk but a constant risk unbiased predictor of a subsequent spot price at least in a long run. However, the trading restrictions and regulatory reforms in 2015 have negatively affected the efficiency of futures market.

1.3 Research Contribution

This thesis is one of the first empirical investigations on the efficiency and effectiveness of the Chinese securities index futures market (CSI300 index futures) and it helps to fills several gaps in the literature, and contributed to existing literature in following ways: Firstly, with the rapid development of economic globalization and network information technology, the frequency and extent of fluctuations in financial markets are increasing. Financial institutions often need to dynamically adjust the size and proportion of various asset positions within the trading day (intraday). This study is different from previous literatures, not only analyzes the data at daily level, but comprehensively analyzes data at the intraday level. In particular, we examine the empirical results of the assessment at both daily-, 60-min and 5-min level, with seven years CSI300 index futures data from 2012 to 2018, which is the most complete transaction data in the previous literature.

Secondly, Chinese regulators strictly tightened the rules on stock index futures in 2015 and caused the stock index futures trading volume fall to less than 1% of the original level, and intraday trading costs increased 100 times. The experience of other mature markets suggest that market regulators should gradually relax, rather than significantly tighten, the regulations on futures trading. The reforms in 2015 provide a good case to study the efficiency and hedging effectiveness of CSI300 index futures market under different regulations. In the Chinese stock index futures market, there has been a sudden and significant change in the volume and liquidity in a short period of time. How will the hedging effectiveness change over time? Whether regulators reforms change the price discovery ability of CSI300 stock index futures? This thesis represents the first empirical investigation of these important issues before and after regulation reforms in the CSI300 index futures trading. Based on the study, a tougher government regulation (e.g., the mainly discussed policy implementation in the thesis) will lead to negative effects to the market performance (hedging effectiveness, price discovery and price efficiency), which implicates the market is adjustable via macro-control.

Thirdly, this thesis also examines two different contracts of the CSI300 stock index futures (i.e., continuous in the current month and consecutively in the next month contract), and compares the hedging effectiveness before and after the regulation reforms in 2015. So that the effectiveness differences and policy recommendations for different maturity contracts and different regulations can be obtained. Finally, this study provides a detailed comparison of various empirical estimation methods, tests the main hypotheses of the futures market. In order to provide a general and reliable empirical basis and corresponding policy recommendations.

1.4 Structure and dataset of the thesis

The remainder of this thesis is organized as follows. Chapter 2 examines the hedging effectiveness of stock index futures in China. It has been long argued that facilitating the activities of hedging the value of the underlying asset against potential losses is one of the most important functions of a futures market. In this chapter, we examine the hedging performance of both the constant and time-varying minimum-variance hedge ratio and assess the hedging effectiveness of CSI300 index futures contracts within the Minimum-Variance Hedging framework.

Chapter 3 discusses the price discovery performance of CSI300 index futures market. Whether price reflects the fundamental value of a security is one of the fundamental questions in finance. And this chapter discusses how efficiency the price discovery is measured in CSI300 index futures market. We employ three different information share methods (i.e., Gonzalo–Granger Permanent–Temporary Measure, Hasbrouck IS Measure, and the Modified Information Share Measure) to investigate the price discovery capability of CSI300 index futures market and compare it to that of with other more mature stock index markets around the world.

Chapter 4 investigates the impact of regulatory reforms on the efficiency of the Chinese index futures market. According to unbiasedness hypothesis, futures prices should be unbiased predictors of subsequent spot price only if both market efficiency condition and no risk premium condition hold. This chapter analyses the market efficiency hypothesis and unbiasedness of futures price hypothesis and presents an empirical investigation of efficiency of CSI 300 stock index futures market, before and after the major regulation reforms in 2015.

Finally, chapter 5 concludes the thesis by summarizing our main findings, making some recommendations for future research in this area, and discussing the implications of our results for investors and market regulators alike.

With regard to the data in our thesis, the datasets of prices with different frequency (e.g., daily, 60min, 5min, etc.) for CSI 300 index and index futures are obtained from the China Financial Futures Exchange (CFFEX). The sample period starts from January 1th, 2012 to December 31th, 2018. The starting date of the sample period is one month after the inception of CSI 300 index futures trading. Data of the first month are excluded from our sample as it takes time for the newly established index futures market to stabilize. A continuous time series for futures prices is constructed by using prices of the nearby futures contract follow the Detail Trading Rules of CFFEX[6]. We specify the nearby futures contract as IF1, the Index Futures of 1-month maturity, the contract with the nearest active trading delivery month (contract month) to the day of trading. There are four CSI 300 index futures contracts being traded simultaneously. Thus, the nearby contract is the contract that expires in the current calendar month. Prices for the nearby futures contract are used until the contract reaches several working days before its expiration date. Specifically, when the volume of IF2 (the Index Futures of 2-month maturity) is greater than the volume of IF1, prices of the next nearby contract (IF2) are used instead. According to the volume rule, mostly prices within 1 to 4 working days before the expiration are abandoned to avoid any unexpected price fluctuation during the delivery event. As for other global market, the data are collected from Reuters with the same construction method mentioned above.

[6] http://www.cffex.com.cn/u/cms/www/202001/22181801axwc.pdf

Chapter 2 - The Hedging Effectiveness of CSI300 Stock Index Futures

2.1: Introduction

2.1.1 Research Background

One of the most important functions of a futures market is to facilitate the hedging activities of the value of the underlying asset against potential losses. Over the past two decades, with the development of the derivatives markets, much of the literature has focused on techniques to reduce investment risk. One simple technique for this purpose is hedging with futures contracts, which despite its simplicity has received extensive research attention (Johnson, 1960; Ederington, 1979; Myers & Thompson, 1989; Cheung et al., 1990; Chen et al., 2003). A key question for hedge is how to determine the optimal hedge ratio, i.e. how many futures contracts should be held for each unit of asset. The calculation of the optimal hedge ratio has been widely documented and discussed in the literature. However, empirical results of the best way to obtain the optimal hedge ratio remain controversial.

In the actual operation of using stock index futures for stock index hedging, the most important question that hedgers must answer is: how many futures contracts should be used to carry out spot products, in order to minimize the risk of spot volatility (variance)? The method of calculating Minimum-Variance Hedge Ratio (MVHR) is the answer to this question. MVHR is defined as the ratio of the number of futures to the number of spots in the hedging operation. It is clear that using different hedge ratios will reduce spot risk (variance) differently. In order to measure the degree of reduction in spot risk (variance) caused by different hedging methods and hedging ratios, Ederington (1979) proposed a measure of hedging effectiveness, which bases on MVHR. This method of hedging effectiveness is the ratio of the variance of the hedge portfolio to the spot variance without hedging (i.e., unhedged portfolio). And the hedge portfolio is made up of the spots and the futures determined by the hedge ratio.

One classical way in the literature to estimate the optimal hedge ratio is by regressing the spot returns against the futures returns using the ordinary least squares (OLS) method (see e.g., Johnson, 1960; Stein, 1961; Ederington, 1979; Benet, 1992). This approach postulates that the objective of hedge is to minimise the variance of the hedged portfolio, thus the hedge ratio that minimises the portfolio variance should be the optimal hedge ratio. In addition to the OLS hedging model, there are other studies using more complex methods to generate the optimal hedge ratio that maximises the expected utility of hedgers or consider the downside risk in the hedged portfolio, such as the mean-Gini coefficient hedging (Chen et al., 2001), the generalised semi-variance hedging (Lien and Tse, 2002), and the lower partial moment (LPM) methodology (Lien, 2004). These studies estimate the optimal hedge ratio under the assumption that the joint distribution of the spot and futures prices is not time-variant. The optimal hedge ratio is not adjusted continuously on the basis of available information in the past.

However, the constant hedge ratio might be sub-optimal if the variance and covariance matrix of the spot and futures returns are conditional on the past available information. The time-varying feature of financial volatility time-series is well-documented and is referred to as the autoregressive conditional heteroskedasticity (ARCH) (Engle, 1982) and the generalised ARCH (GARCH) (Bollerslev, 1988). Various bivariate generalised autoregressive conditional heteroskedasticity (BGARCH)-type models have been utilised to estimate the time-varying hedge ratios (see, e.g., Baillie and Myers, 1991; Brooks et al., 2002; Lien et al., 2002). The time-varying hedge ratio is distinguished from constant hedge ratio because it is conditional on the information set available at the previous time period. The hedged portfolio constructed from the time-varying hedge ratio is adjusted on a regular basis to reflect information set available at the time the hedging decision is made.

Although the time-varying hedge ratio captures the time-varying second moments of financial time series, there is a debate as to whether the conditional (time-varying) hedging model can outperform the unconditional (constant) hedging model. Some studies conclude that the time-varying hedge ratio generates a higher variance reduction than the conventional constant hedge ratio (e.g., Baillie and Myers, 1991; Bhar et al., 2001; Park and Switzer, 1995). Other studies find that employing a time-varying hedging model does not provide a significant improvement for the futures hedge compared to a constant hedge model (e.g., Lien et al., 2002). Park and Switzer (1995) further claim that a time-varying hedging model can make the modest improvement relative to a constant hedging model when the standard deviation of the time-varying hedge ratio is stable and low enough. However, even if such improvement exists, it cannot guarantee that a time-varying hedging model is superior to a constant model. If transaction cost is considered, the benefits of the conditional hedge could be shrunken.

Figlewski (1985), Lee (1987), Benet (1992) and Cecchetti (1988) point out that the static hedge ratio calculated by ordinary least squares (OLS), vector autoregressive (VAR) or vector error correction model (VECM) has better risk hedging efficiency. However, in recent years, using more empirical studies, Baillie (1991), Myers (1991), Kroner (1993), Park (1995), and Choudhry (2003) have found that using multivariate conditional volatility models (such as multivariate generalized autoregressive conditional heteroscedasticity model, MVGARCH) can more realistically characterize the conditional volatility and conditional correlation between spot and futures. As a result, a better hedging effectiveness would be achieved through the dynamic strategies.

In China, Ma (2000), Wang (2009) and Fu (2009) also use various hedging models to conduct a comparative study of relevant hedging efficiency. Using the convexity index of bonds, Yang (2005) has analyzed the pricing relationship between Treasury bond futures and its cheapest delivery bond and put forward an analytical method to calculate the optimal hedging ratio. Fu (2010) uses state space model to study the optimal hedging efficiency of Chinese copper futures market, and compares it with other traditional hedging methods. Lien (2009) has provides a comprehensive overview of the efficiency issues of various hedging models. Hsu (2008) pointed out that various forms of dynamic MVGARCH models assume that the joint distribution of spot and futures follows a multivariate normal distribution with linear correlation. However, the actual financial asset returns often exhibit skewed, leptokurtic and fat-tailed and asymmetric nonlinear dependence. Therefore, Hsu (2008) argued that these stylized facts of financial markets must be taken into account when calculating the hedge ratio.

The motivations behind this study is to provide further empirical evidence on these contradictory results and to analyze whether more complex models better fit the financial series patterns and provide superior hedging effectiveness. Take the Chinese index futures for example, Chinese stock and index futures market are developing very fast in last 20 years, but investors have a rather limited understanding on how to estimate and evaluate risk. The results of this chapter would help investors to select appropriate positions in the Chinese futures market to offset the risk from corresponding holdings in the spot market.

2.1.2 Research Aim and Objective

The China Securities Index (CSI) 300 futures market has received much attention since it was launched on April 16, 2010. Specifically, as the first stock index futures contract being traded in the mainland, investors have paid a close attention on the CSI300 index futures in order to predict the future spot prices and to minimize risk of spot asset. However, the number of studies that focus on the performance of CSI300 index futures contracts in hedging risk of spot asset is rather limited in the literature. Although there are a few studies on the functionality of hedging with the Chinese index futures contracts (see, e.g. Fu et al., 2010; Wei et al., 2013), their sample period is very limited, and dataset is also relatively small. For instance, Fu et al. (2010) examines simulation data and the sample period of Wei et al. (2013) covers only one year from 2010 to 2011. Besides, the empirical results of these studies are also contradicting and inconclusive. Thus, a more thorough investigation of the performance of the newly established CSI 300 index futures contract as a hedging tool is needed and warranted.

As mentioned above, there is no consensus on which method should be used to calculate the optimal hedging ratio. In addition, the CSI300 stock index futures market has just been launched several years and the question of which methods should be used to carry out effective hedging operations is an important issue worthy of attention. In particular, compared with the mature market and the surrounding emerging markets, how effective it is in hedging with CSI300 stock index futures? It is also important to analyze how much risk the CSI 300 stock index futures can hedge against the spot index. Finally, whether the hedging effectiveness of CSI 300 Index futures contracts at different maturities may differ? While Li (2010) and Liang (2009) have attempted to carry out an initial investigation in the area, there is a lack of rigorous and systematic analysis in addressing the above-mentioned issues in the Chinese market.

In this chapter, based on both daily and intraday data of CSI 300 stock index futures, we examine the hedging performance of the constant and time-varying hedge ratios using the variance reduction as the performance benchmark. More specifically, we aim to address the following research questions:

- Whether, and to what extent, CSI300 index futures contract provides investors with an effective hedging tool?
- Whether the regulation reforms in 2015 have affected the hedging effectiveness of CSI300 index futures?
- Whether or not the hedging effectiveness of CSI300 index futures would be dependent on data frequency and contract maturities?

2.1.3 Research Significance

This chapter is one of the first attempts in empirically investigating the hedging effectiveness of the Chinese stock index futures. It has been argued that, due to its (lack of) maturity, the price discovery ability of CSI 300 stock index futures is weak and the risk hedging effectiveness is low compared with index futures contracts in other mature markets (Wei, 2013). In addition, Fu and Zhang (2010) also indicate that the next month contract of CSI300 stock index futures has a better intraday risk hedging effectiveness than the current month contract, contradicting the traditional hedging theory.

Taken together, this chapter contributed to existing literature in following ways. Firstly, with the rapid development of economic globalization and network information technology, the frequency and extent of fluctuations in financial markets are increasing. Financial institutions often need to dynamically adjust the size and proportion of various asset positions within the trading day (intraday). Therefore, it is more and more important to discuss the hedging strategy of stock index futures in the high frequency environment. Further, given that the CSI 300 stock index futures was launched in 2010, the high-frequency data of the CSI 300 index and index futures contracts is used in this chapter to obtain the larger possible data sample for our empirical analysis. Unlike the existing researches on CSI300 stock index futures which use daily data, this chapter employs the complete intraday data of CSI300 index futures between 2012 and 2018. In particular, we use not only the daily data but also intraday data at 5-min and 60-min level to study the hedging effectiveness of CSI300 index futures, and examine whether the main results are dependent on the frequencies of data.

Secondly, in 2015 the market regulators strictly tightened the rules of stock index futures trading in China and caused the stock index futures trading volume fall to less than 1% of the initial trading volume. These regulatory reforms however provide us with a good opportunity to further investigate the relationship between market regulations and hedging effectiveness of stock index futures market. For instance, how will the hedging effectiveness be affected by the reforms in 2015? Whether regulatory reforms significantly change the hedging effectiveness of CSI300 stock index futures? This chapter represents one of the first attempts in analyzing the hedging effectiveness of CSI300 index futures before and after regulators reforms.

Thirdly, this chapter examines the hedging ratio and effectiveness of the two types of contracts of the CSI300 stock index futures (i.e. continuous in the current month and consecutively in the next month contract), and compares the hedging effectiveness before and after the regulation reforms in 2015. So that the hedging effectiveness for different maturity contracts and effective policy recommendations can be obtained.

Finally, this chapter provides a detailed comparison of various estimation methods (such as OLS, VAR, VECM, Diagonal-MVGARCH, BEKK-MVGARCH, CCC-MVGARCH and DCC-MVGARCH models) in order to provide a comprehensive and reliable empirical basis and recommendation for the calculation of hedging ratio and the measurement of hedging effectiveness of CSI 300 stock index futures. Specifically, we compare the hedging performance of both constant and time-varying hedging models in hedging underlying stock market risk. By considering various hedging horizons, this study also unveils interesting facts about CSI 300 index futures market.

2.1.4 Outline and Structure

The rest of the chapter is organized as follows. The section 2.2 provides a brief review of literature on the theory of hedging and minimum-variance hedge ratio (MVHR) methodology. Section 2.3 discusses the constant and time-varying hedge ratios. The empirical results are then presented and analyzed in section 2.4. Finally, section 2.5 concludes the chapter.

2.2: Literature Review

It has been long argued that hedging is one of the most important social functions of futures markets (Working 1953). However, although hedging is believed to be the main reason for trading futures contracts, the objective of hedging has been proved controversial. This section sets out the alternative views of the purposes of hedging and, following that, presents the derivation of the minimum-variance hedge ratio.

2.2.1 The Theories of Hedging

The origin of the term 'hedging' is unclear, but it appears to derive from the use of hedges to form a protective or defensive barrier around property (see Arditti, 1996). The objectives for hedging are as many as there are the potential risks in the market. In discussing hedge theory, Sutcliffe (1997) lists three main views of the nature and purpose of hedging: Firstly, the traditional risk minimization view, where traders are seeking to reduce price risk. Secondly, the profit maximization view, where traders attempt to profit from the expected movements of the spot and futures price. Thirdly, the portfolio approach, where traders try to reach a satisfactory risk-return trade-off by diversification. Each of these interpretations is considered next.

2.2.1.1 Risk Minimization

Risk minimization refers to an investor who is exposed to a risk and wishes to minimize or eliminate this exposure as his or her primary goal. This is normally achieved by taking an additional investment whose risk cancels out the initial risk. The investment of both the initial asset and the futures used to offset the risk of this asset must be at equal magnitude. The hedge ratio (i.e. the number of derivatives contracts bought or sold divided by the number of spot contracts whose risk is being hedged) is simply one-to-one. In this case, the price of the derivatives contract and the price of the spot asset to be hedged are assumed to be perfectly correlated so that the losses on one position can be completely offset by the gains on the other position. In other words, this traditional view assumes that hedging will eliminate price risk. However, in reality, there is always a small amount of risk that remains unhedged when hedging with derivatives. A 'perfect' hedge will only occur when the risk of the additional investment exactly offset the initial risk. Unfortunately, Chinn and Coibion (2013) indicated that derivatives and spot prices do not move in unison due to a range of economic reasons, such as lack of storage, rules and regulations shortage, and fundamental changes.

2.2.1.2 Profit Maximization

Working (1953) was the first to challenge the traditional risk minimization view of hedging, and to suggest that hedging in practice is undertaken not only for risk minimization but also for other business-related reasons such as profit maximization. He argues, in the context of commodity futures, that role of risk-avoidance in most commercial hedging has been greatly overemphasized in economic discussions. The merchants buy the spot commodity because the spot price is low relative to the futures price, and he has reason to expect the spot premium to advance. Under this interpretation, the objective of a hedge is not to minimize risk, but to make a profit from movements in the relative prices of the spot asset and derivatives contract (i.e., speculation on the basis). Thus, Working (1953) views hedging as a form of arbitrage and explicitly considers the speculative aspect of hedging.

2.2.1.3 Portfolio Approach

Based on the earlier work of Johnson (1960) and Stein (1961), Ederington (1979) argues that a portfolio approach to hedging is superior to both the traditional one-to-one risk-minimizing and the profit-maximizing hedging interpretations. Under the mean-variance portfolio approach, the hedgers are assumed to be risk-averse and can hold different positions of the cash (long) and derivatives contracts (short) in his/her portfolio with the objective of maximizing the expected value of the utility function. The investors buy or sell derivatives contracts in the same way they buy or sell any other portfolio of assets, according to their risk-return preferences. Therefore, a portfolio with assets and/or derivatives contracts can be entirely or partially hedged, depending on the risk and return the investor wants to sustain or earn. If an investor wants more earnings, he/she must also be willing take a higher risk. The portfolio strategies offer an opportunity for the hedger to select from a range of expected returns (i.e. diversify) because this approach does not require a cash portfolio to be fully hedged in order to lock in the existing returns (Howard and D' Antonio. 1991). This view of hedging incorporates both risk minimization and profit maximization as the objectives of hedgers.

2.2.2 Measurements of MVHR and Hedging Effectiveness

The discussion above demonstrates that, although alternative hedging strategies have been proposed to explain the purposes of hedging, the general view of hedging is that it is a means of protecting or ensuring a position held in spot market. In spite of the restrictive assumption regarding attitudes to risk (i.e. infinite risk aversion), the risk-minimizing approach provides a benchmark against which hedging effectiveness can be assessed and has been widely used in the literature (see Figlewski, 1984; Lindahl, 1992; Holmes, 1996; and Butterworth and Holmes, 2001). Therefore, the empirical analysis in this chapter is also undertaken on the basis that the primary purpose of hedging is to minimize the risk of a cash position.

To achieve the risk minimization objective, the hedger has to determine the number of futures contracts to buy or sell for each unit of spot asset on which he/she bears price risk (i.e. hedge ratio) that minimizes the hedge portfolio risk. Johnson (1960), Stein (1961), and Ederington (1979) apply the principles of portfolio theory to demonstrate that the hedge ratio that minimizes the risk of the hedged position is given by the ratio of the unconditional covariance between spot and futures price changes over the unconditional variance of futures price changes.

Assume that an individual has taken a long position in one unit of a particular spot and wants to secure his existing return by taking a short position in futures market. The percentage log yields return for spot and futures as on the hedged portfolio are given by:

$$\begin{aligned} RS_t &= 100 \times (S_t - S_{t-1}) \\ RF_t &= 100 \times (F_t - F_{t-1}) \\ S_t &= \ln(spotprice)_t \\ F_t &= \ln(futureprice)_t \end{aligned} \qquad (2.1)$$

where S_t and F_t are the natural logarithm spot and futures price during time t; Johnson (1960) proposed a method for calculating the Minimum-Variance Hedging Ratio (MVHR), which is given by:

$$MVHR = \frac{\sigma_{sf}}{\sigma_f^2} = \frac{Cov(RS, RF)}{Var(RF)} \qquad (2.2)$$

where σ_{sf} is the covariance of the spot and futures returns; σ_f^2 is the variance of the futures return. When time t from 1 to n, the returns of natural logarithm spot form a group RS_t, $RS = (RS_1, RS_2, \ldots RS_t)$, and the returns of natural logarithm futures form another group RF_t, $RF = (RF_1, RF_2, \ldots RF_t)$,

From the perspective of portfolio theory, hedging can be seen as adding a certain number of futures positions to the spot position, thereby reducing the risk (variance) of the entire portfolio.

According to Ederington (1979), hedging effectiveness (*HE*) can be calculated by the following series of formulas. First, the spot position yield without hedging (R_U) and the hedging portfolio yield (R_H) after hedging through futures can be defined as

$$
\begin{aligned}
R_U &= RS \\
R_H &= RS - MVHR \times RF
\end{aligned}
\quad (2.3)
$$

Then, the variance of portfolios with hedging and without hedging are:

$$
\begin{aligned}
Var(R_U) &= \sigma_s^2 \\
Var(R_H) &= \sigma_s^2 + (MVHR)^2 \sigma_f^2 - 2MVHR * \sigma_{sf}
\end{aligned}
\quad (2.4)
$$

Ederington (1979) shows that, in summary, the hedging effectiveness (*HE*) can be defined as the ratio of the spot variance reduction after joining the futures hedging, ie

$$HE = \frac{Var(R_U) - Var(R_H)}{Var(R_U)} \quad (2.5)$$

As can be seen from the above definition, *HE* is a positive number between 0 and 1. The larger the value, the more accurate the corresponding hedge ratio, and the more the variance (risk) of the spot is reduced, the higher the hedging effectiveness of the hedging method adopted.

2.2.3 Traditional static and dynamic hedging models

The pioneering work using constant hedge ratios was performed by Ederington (1979). In this approach, the hedge ratio ($\mathrm{HR} = \sigma_{sf}/\sigma_f^2$) is estimated through the slope of the ordinary least squares (OLS) regression between the spot and futures returns. However, this approach exhibits several problems. One problem is that it does not account for the short-run disequilibrium between the spot and futures markets (Ghosh, 1993; Lien, 1996). This can be attributed to the fluctuations of price spread for futures and spots in short-run. Another problem is that it assumes constant conditional second-order moments; therefore, static hedging is not conditional on the arrival of information into the market.

In general, there are two approaches main in estimating dynamic hedge ratios. The first approach consists of allowing the hedge ratios to be time-varying coefficients and estimating these coefficients directly (Alizadeh & Nomikos, 2004; Lee et al., 2006). The second approach (Kroner & Sultan, 1991; Brooks et al., 2002) uses the conditional second-order moments of the spot and futures returns from multivariate GARCH models, which allow for the estimation of hedge ratios at time t adjusted for the information set available to the investor at *t-1*: $HR_t = \frac{\sigma_{sf}}{\sigma_f^2} | \Omega_{t-1}$. Most of the literature has focused on this second approach, proposing increasingly complete models that more accurately capture the characteristics of the financial data and thereby overcome the limitations of the simpler GARCH models. One of the limitations of GARCH model is that they are incapable of reliably capturing the patterns of financial data series, specifically the asymmetric impact of news (Engle & Ng, 1993; Glosten et al., 1993; Kroner & Ng, 1998). Negative shocks are widely known to have a greater impact on financial series than positive shocks. This fact should be taken into account when the hedge ratios are estimated. Brooks et al. (2002) conclude that hedging effectiveness is greater when this asymmetric behavior is considered. Another limitation of GARCH models is that they consider high-volatility persistence. This high persistence level suggests the absence of regimes in the volatility process (Marcucci, 2005). Ignoring these regime shifts could lead to inefficient volatility estimations. Therefore, the consideration of regimes in the volatility process could lead to more accurate estimations of volatility and, thus, a better performance for hedging strategies.

Cotter & Hanly (2006), for instance, consider the slope of the OLS regression between spot and futures returns (minimum variance hedge ratio) to be regime dependent. Alizadeh and Nomikos (2004) were the first to use this methodology to estimate time-varying hedge ratios. Chen and Tsay (2011) use a similar methodology to include the state-dependent autoregressive terms of the spot and future returns. In all of these studies, the regime-switching is considered in the mean equation, assuming the variance to be constant over time but dependent on the state.

Another way to consider the regime-switching influence on the optimal hedge ratio estimation is through regime-switching-GARCH models (RS-GARCH) (Lee & Yoder 2007a,b; Alizadeh et al., 2008; Lee, 2009a,b; Lee, 2010). Lee and Yoder (2007a) first consider a regime-switching time-varying correlation model. Then, Lee and Yoder (2007b) develop a new MRS-BEKK model in which they extend the work of Gray (1996) to the bivariate case. These studies propose a method for conditional covariance matrices that allow the models to be tractable. They focus on modeling the variance and disregard the behavior of the mean. Alizadeh et al. (2008) incorporate an error correction term (ECT) that allows the series characteristics to be related in the short and long run. These previous studies consider both time varying and state-dependent conditional variances in estimating the optimal hedge ratio.

Despite the popularity and success of the above methods and their various extensions, the time-varying hedging strategy does not always provide a better hedging effectiveness than that of a simple static hedging strategy. First, traditional static hedging models (such as OLS and VECM) fail to incorporate the higher moments properties of most financial asset return series and demonstrate that the out-of-sample performance of the hedging strategy which considers the information in the higher moments is better than the performance using OLS method. Another problem pointed out by Ghosh (1993) and Lien (1996) is that the classic least square regression ignores the disequilibrium error in the short-term dynamics. Lien (1996) shows that the omission of the co-integration relationship leads to a smaller hedging position and, therefore yields a relatively poor hedge performance. Subsequent studies, such as Lien (2004, 2009), provide further evidence of the reduction in hedging effectiveness caused by omitting the error correction term. These findings suggest that an error correction model (ECM) should be used when estimating optimal (unconditional) hedge ratios. However, this method has been criticized for ignoring the time-varying changes in the joint distribution of spot and future prices.

As a result, alternative methods for estimating optimal time-varying hedge ratios, such as the random coefficient model or the bivariate generalized autoregressive conditional heteroscedasticity (GARCH) model, are more widely used. Previous studies, such as Cecchetti, Cumby, and Figlewski (1998), Baillie and Myers (1991), and Myers (1991), argue that the time variation of optimal hedge ratio may come from the conditional heteroscedasticity in the spot and futures returns. Thus, multivariate GARCH models have been adopted to estimate conditional hedge ratios, for example, by Baillie and Myers (1991), Brooks, Henry, and Persand (2002), Kavussanos and Nomikos (2000b), Harris and Shen (2003), Hsu, Tseng, and Wang (2008), Miffre (2004), and Park and Jei (2010). Other related studies include those of Myers (1991), Kroner and Sultan (1993), Park and Switzer (1995), Garcia, Roh, and Leuthold (1995), Bera, Garcia, and Roh (1997), and Moschini and Myers (2002), among many others. In contrast, Grammatikos and Saunders (1983) regard the optimal hedge ratio as a random state variable that follows an autoregressive or other stochastic process. In this case, the optimal hedge ratio can be estimated using the random coefficient model (RCM), as discussed in Bera, Garcia, and Roh (1997), and Chang, Lai, and Chuang (2010). Kavussanos and Nomikos (2000b) show that these conditional hedge ratios provide larger variance reduction than static hedge ratios.

In addition, the economic theory suggests that the prices of the spot asset and the derivatives contract are jointly determined (see, e.g., Stein, 1961). Estimating the spot and futures prices separately will be subjected to the “bias” (Power, G. J., & Vedenov, D. V.,2008; Chevallier, J., 2010), which leads to upward biased and inconsistent estimated hedge ratio. Furthermore, equation (2.2) is potentially mis-specified because it ignores the existence of a long-run cointegration relationship between spot and futures prices, and fails to capture the short-run dynamics by excluding relevant lagged variables (Engle and Granger, 1987). Omitting both long-run and short-run dynamics in the spot-future system will lead to downward bias on the estimated *MVHR*, which could possibly suffer from the problem of serial correlation in the regression residuals. As a result, the futures position is less than optimal (see, for example, Herbst et al. 1992; Chou et al. 1996; Lien, 1996; and Lien, 2004).

Finally, in equation (2.2) it is assumed that the covariance and the variance of futures returns remain constant over time. Clearly, this assumption is too restrictive and in contrast with the empirical evidence documented in various markets, indicating that spot and futures are characterized by time-varying distributions (see, e.g. Park and Switzer, 1995). The findings of these studies suggest that the optimal (i.e. risk-minimizing) hedge ratios should also be time-varying because the variance and covariance entering the *MVHR* calculations in equation (2.2) will adjust continuously as the new information arrives in the market.

The preceding discussion highlights the concerns regarding to the risk reduction properties of the *MVHR*, which are generated from equation (2.2). In order to address these problems, recent empirical studies have started to model the spot and futures returns as a vector error-correction model (VECM) with the GARCH error structure. The VECM captures both short- and long-run relationships between spot and futures prices, while GARCH error structure permits the second moments of their distribution to change over time (see Gagnon and Lypny, 1997; Choudhry, 2003).

For instance, Kroner (1993) pointed out that the multivariate GARCH model (MVGARCH) can be used to model the conditional returns of spot and futures. At the same time, in order to characterize the long-term cointegration relationship between spot and futures prices, Kroner (1993) proposed a multivariate GARCH model based on VECM (VECM-MVGARCH). Subsequently, Lien (1996) Thomas (2001) and Hsu

(2008) characterize the time-varying characteristics of the conditional variance-covariance matrix of MVGARCH from different angles, and developed diagonal, BEKK, and often MVGARCH models in the form of conditional correlation (CCC) and dynamic condition correlation (DCC).

Considering the time-varying characteristics of the conditional variance-covariance matrix, the dynamic hedge ratio based on the MVGARCH model is defined as the dynamic hedge ratio based on the static hedging ratio shown in equation (2.2).

$$MVHR_t = \frac{\sigma_{sf\,t}}{\sigma^2_{f\,t}} = \frac{Cov(RS_t, RF_t)}{Var(RF_t)} \qquad (2.6)$$

Similarly, the hedging effectiveness under dynamic hedging ratio can be calculated by Equation (2.3) - (2.5).

$$HE_t = \frac{Var(RS_t) - Var(RS_t - MVHR_t \times RF_t)}{Var(RS_t)} \qquad (2.7)$$

Many studies have discussed methods for evaluating optimal static (unconditional) and time-varying (conditional) hedge ratios. The most widely used optimal hedge ratio is the minimal-variance ratio, defined as the covariance between the spot and futures returns divided by the variance of the futures returns.

There are some other studies that consider nonparametric time-varying models. Robinson (1989) studies a nonparametric time-varying regression model. Orbe and Ferreira (2005) investigate a single-equation regression model using time-varying coefficients with seasonal patterns and locally stationary time-series variables. Then, Cai (2007) uses the local polynomial regression method of Fan and Lee (1996) to estimate the time-varying coefficients in the regression model. Li and Yang (2011) and Ang and Kristensen (2012) consider conditional asset pricing models in which the time-varying betas are assumed to be a smooth function of the time index, and find strong evidence against the constancy of regression coefficients. Furthermore, Ferreira, Gil-Bazo, and Orbe (2011) assume that the conditional betas in the three-factor model of Fama and French (1993) are a smooth function of index variables, such as dividend yields or the term spread. They find that the estimated conditional betas outperform the betas obtained from the rolling window scheme under different specifications of beta dynamics.

Recent studies show that the conditional hedge ratios estimated by GARCH or random coefficient models are too volatile to outperform the static optimal hedge ratio, especially in terms of the out-of-sample performance (Kavussanos and Nomikos, 2000a; Lien, 2002, 2005, 2008). Lien (2002) finds that the conditional hedging strategy cannot outperform the OLS hedging scheme. Lien (2008) provides a theoretical proof that the OLS hedging strategy dominates any dynamic strategy in terms of the post-sample hedging performance. Moreover, Kavussanos and Nomikos (2000a) find that the hedge ratio has to be sufficiently volatile to outperform the OLS strategy. However, using various flexible GARCH models, Park and Jei (2010) present empirical evidence of an inverse relationship between the variability of the hedge ratio and hedging effectiveness, while Lien (2010) analyzes the inverse relationship between hedge ratio variability and hedge performance from a theoretical point of view. Thus, a conditional hedge strategy with a high degree of variability is unlikely to outperform the OLS hedging scheme.

Table 2.1 A Brief Summary of Key Empirical Studies on Hedging Effectiveness

Studies	Market	Data	Empirical models
Lien (2000a,2000b)	S&P 500, Nikkei 225, Currencies (British pound, Deutschemark, Japanese yen)	Weekly from 1988 to 1996	Static models
Conclusion: In large sample cases, the conventional hedge ratio provides the best performance.			
Kavussanos et al. (2000a)	BIFFEX	Daily from 1992 to 1997	Static models
Conclusion: GARCH provides greater risk reduction than a simple constant hedge ratio. However, it fails to eliminate the riskiness of the spot position to the extent evidenced in other markets in the literature. This is thought to be the result of the heterogeneous composition of the underlying index.			
Cotter and Hanly (2006)	S&P 500, DAX30, Nikkei225, CAC40, DJI, Hang Seng futures	Daily from 1998 to 2003	Static models
Conclusion: The overall dominance of Naive and OLS hedge strategies is not specific to the use of the variance as a method of evaluating hedging performance.			
Park and Jei (2010)	Soybean Oil futures and Corn futures	Daily from 1997 to 2001	Static models
Conclusion: Some BGARCH hedging strategies may have modest improvements when their standard deviations are stable and low enough. However, the improvement is not big enough to guarantee that a BGARCH hedging strategy is superior to OLS hedging strategy.			
Myers (1991)	Wheat futures at CBOT	Daily from 1977 to 1983	Dynamic models
Conclusion: GARCH model provides superior hedging performance than either the constant hedge ratio model or the moving sample variances and covariances model.			

Park & Switzer, (1995)	S&P 500 and Toronto 35 Index Futures.	Daily from 1988 to 1991	Dynamic models
Conclusion: If the joint distribution of stock index and futures prices is changing through time, estimating a constant hedge ratio may not be appropriate.			
Brooks et (2002)	FTSE 100 stock index and futures	Daily from 1985 to 1999	Dynamic models
Conclusion: Allowing for asymmetries leads to considerably reduced portfolio risk at the shortest forecasting horizons and modest benefits when the duration of the hedge is increased.			

The list of a brief summary for key empirical studies on hedging effectiveness with papers, market, time period and empirical models.

2.2.4 Recent Studies on Hedging Effectiveness of CSI300

As CSI300 index futures was only introduced in 2010, academic research on the hedging effectiveness of CSI300 index futures are relatively limited. This chapter aims to employ both traditional static and dynamic models to examine its hedging effectiveness. Wen (2011) shows that CSI300 index futures prices are cointegrated with spot prices and are unbiased predictors of future spot prices. Based on daily data, hedging effectiveness of CSI300 index futures is about 91%, which can help investors to avoid the systematic risk in the spot market well. Wen (2011) shows that the static OLS model performs best in reducing variance. Dynamic hedging models are unstable and transaction costs are high. Wei et al. (2011) uses intraday data and indicates that multifractal analysis may offer better hedging model design. Furthermore, Hou (2013) also find that the CSI 300 stock index futures can be an effective hedging tool. The question whether time-varying ratios outperform constant ratios depends on the length of the hedging horizon. Short horizon is likely to favor dynamic BGARCH hedging models while long horizon tends to favor constant hedging ratio models. Furthermore, comparing the different time-varying ratio models, DCC model is better with short hedging horizons and CCC model is more favorable with long hedging horizons.

Using 5-min intraday data, Qu (2018) shows that the dynamic hedging performance consistently dominates the conventional methods in terms of performance measures including the hedge ratio, the hedging effectiveness, the portfolio returns and the Sharp ratio. Furthermore, the dynamic methods are consistent during different periods of fluctuations in Chinese financial markets, including turbulent period in 2015.

Table 2.2 A Summary of Studies on CSI300 Index Futures Hedging Effectiveness

Studies	Frequency of Data	Estimating Methods	Empirical Models
Wen (2011)	Daily	OLS and GARCH	Traditional static OLS model
Wei (2011)	Intraday at 5-min level	copula–MFV & copula–GARCH	Neither static nor dynamic, but multifractal models
Hou (2013)	Daily	Naive, OLS, EC and GARCH	Depends on the length of the hedging horizon (static models in long and dynamic models in short)
Qu (2018)	High-frequency intraday	Realized-HAR	Dynamic models

The list of a summary for studies on CSI300 Index futures hedging effectiveness with papers, market, time period and empirical models.

The literature reviewed above shows that there are advantages and disadvantages of traditional static and dynamic hedging models, however, there is no consensus as to which approach is better in identifying and estimating the optimal hedge ratio. This chapter will therefore aim to shed further light on this issue by examining and comparing the effectiveness of traditional static and dynamic hedging models in the Chinese index futures market.

2.3: Methodology

According to Ederington (1979), the hedging effectiveness (*HE)* can be defined as the ratio of the spot variance reduction after joining the futures hedging as defined by *MVHR* and $MVHR_t$ in equation (2.4) and (2.5). As can be seen from the above definition, *HE* is a positive number between 0 and 1. The larger the value, the more accurate the corresponding hedge ratio, and the more the variance (risk) of the spot is reduced, the higher the hedging effectiveness of the hedging method.

The static hedging models employed in this chapter are OLS and VECM. The dynamic hedging models include BEKK, CCC and DCC. Next, we will discuss each of these hedge ratio estimation methods in details.

2.3.1 Static Hedging Models

2.3.1.1 OLS Model

Ordinary least squares (OLS) is a type of linear least squares method for estimating the unknown parameters in a linear regression model. In this approach, the hedge ratio is σ_{sf}/σ_f^2. This hedge ratio is estimated through the slope of the ordinary least squares regression between the spot and futures returns. OLS chooses the parameters of a linear function of a set of explanatory variables by the principle of least squares: minimizing the sum of the squares of the differences between the observed dependent variable (values of the variable being predicted) in the given dataset and those predicted by the linear function.

Let S_t and F_t denote, respectively, the logarithm of spot and futures prices at time t. The spot and futures returns are calculated as $RS_t = 100 \times (S_t - S_{t-1})$ and $RF_t = 100 \times (F_t - F_{t-1})$. The basis (i.e. spread) is defined as $S_t = \alpha F_t + \beta + \varepsilon$, α & β are parameters.

$$RS_t = \alpha * RF_t + \beta + \varepsilon$$

$$\begin{aligned} RS_t &= 100 \times (S_t - S_{t-1}) \\ RF_t &= 100 \times (F_t - F_{t-1}) \\ S_t &= \ln(spotprice)_t \\ F_t &= \ln(futureprice)_t \end{aligned} \qquad (2.1)$$

Johnson (1960) proposed a method for calculating the Minimum-Variance Hedging Ratio (*MVHR*), which is given by:

$$MVHR = \frac{\sigma_{sf}}{\sigma_f^2} = \frac{Cov(RS, RF)}{Var(RF)} \qquad (2.2)$$

where σ_{sf} is the covariance of the spot and futures returns; σ_f^2 is the variance of the futures return. From the perspective of portfolio theory, hedging can be seen as adding a certain number of futures positions to the spot position, thereby reducing the risk (variance) of the entire portfolio.

$$\begin{aligned} R_U &= RS \\ R_H &= RS - MVHR \times RF \end{aligned} \qquad (2.3)$$

Ederington (1979) shows that, in summary, the hedging effectiveness (*HE*) can be defined as the ratio of the spot variance reduction after joining the futures hedging, i.e.,

$$HE = \frac{Var(R_U) - Var(R_H)}{Var(R_U)} \qquad (2.5)$$

However, as discussed above, this approach exhibits several problems. One problem is that it does not account for the short-run disequilibrium between the spot and futures markets (Ghosh, 1993; Lien, 1996). This can be attributed to the fluctuations of price spread for futures and spots. Another problem is that it assumes constant conditional second-order moments.

2.3.1.2 VECM Model

To estimate the $MVHR_t$ in equation (2.6), the VECM models can be employed to account for the cointegrating relationship between spot and futures prices and the dynamic nature of their return distribution. The rationale of using VECM models in estimating futures hedge ratio (MVHR) is that futures and stock index prices react to the same information, and thus, have non-zero covariance conditional upon the available information set. Alternative model specifications that we used in estimating *MVHR* are considered in turn.

Again, let S_t and F_t denote, respectively, the logarithm of spot and futures prices at time *t*. The spot and futures returns are calculated as $RS_t = 100 \times (S_t - S_{t-1})$ and $RF_t = 100 \times (F_t - F_{t-1})$. The basis (i.e. spread) is defined as $B_t = S_t - \alpha F_t$, α is a parameter. A bivariate error correction model (VECM) for the returns is specified as the following form:

$$RS_t = \alpha_{S0} + \sum_{i=1}^{p-1} \alpha_{Si} RS_{t-i} + \sum_{i=1}^{p-1} \beta_{Si} RF_{t-i} + \gamma_S B_{t-1} + \varepsilon_{S,t}$$

$$RF_t = \alpha_{F0} + \sum_{i=1}^{p-1} \alpha_{Fi} RS_{t-i} + \sum_{i=1}^{p-1} \beta_{Fi} RF_{t-i} + \gamma_F B_{t-1} + \varepsilon_{F,t} \qquad (2.8)$$

This VECM specification contains information on both the short and long-run adjustments to changes in spot-futures system. Specifically, B_{t-1} serves as the error correction term to ensure that spot and futures prices never wander far from each other. The importance of incorporating a cointegrating relationship into the statistical modelling of spot and futures prices has been highlighted in many previous studies such as Kroner and Sultan (1993), Lien (1996), Choudhry (2003), and Lien (2004).

$$MVHR = \frac{\sigma_{sf}}{\sigma_f^2} = \frac{Cov(\varepsilon_S, \varepsilon_F)}{Var(\varepsilon_F)} \qquad (2.9)$$

$$HE = \frac{Var(R_U) - Var(R_H)}{Var(R_U)} = \frac{Var(\varepsilon_S) - Var(\varepsilon_S - MVHR * \varepsilon_F)}{Var(\varepsilon_S)} \qquad (2.10)$$

Where $\varepsilon_S = (\varepsilon_{S,1}, \varepsilon_{S,2}, \ldots \varepsilon_{S,t})$, and $\varepsilon_F = (\varepsilon_{F,1}, \varepsilon_{F,2}, \ldots \varepsilon_{F,t})$

2.3.2 Dynamic Hedging Models

It is now well recognized that the variance of asset returns and the covariance among different asset returns are varying over time. To account for this statistical property, multivariate GARCH models are widely adopted to describe the dynamic behavior of variance of spot and futures returns as well as the covariance between them. Different model specifications/restrictions on the conditional variance-covariance matrix in multivariate GARCH model have been introduced to overcome the computational difficulty and to ensure a positive definite variance-covariance matrix. Each model has advantages and shortcomings, and may fit into one set of data better than others (see Bauwens et al., 2006 for an excellent review of multivariate GARCH models).

2.3.2.1 BEKK-GARCH Model

To estimate the conditional variance-covariance matrix of the stock and futures returns, $H_t = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix}$, we utilize the bivariate BEKK-GARCH (1,1,1) model first proposed by Engle and Kroner (1995) where the time-series evolution of H_t, is described as follows:

$$H_t = C_0 C_0^{'} + A_1^{'} \varepsilon_{t-1} \varepsilon_{t-1}^{'} A_1 + B_1^{'} H_{t-1} B_1 \tag{2.11}$$

where, $C_0 = \begin{bmatrix} c_{11} & 0 \\ c_{21} & c_{22} \end{bmatrix}$; $A_1 = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$; $B_1 = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}$

The innovations ε_t in equation (2.11) are the unautocorrelated residuals obtained from our previous VECM in equation (2.8). We specify market 1 to be the spot, market 2 to be the futures. In this specification, there are two variance equations and one covariance equation, with a total of L1 parameters in the conditional variance-covariance system, H_t.

$$
\begin{aligned}
MVHR_t &= \frac{h_{SF,t}}{h_{F,t}} \\
HE_t &= \frac{h_{S,t} - (h_{S,t} + MVHR_t^2 * h_{F,t} - 2 * MVHR_t \sqrt{h_{S,t}}\sqrt{h_{F,t}})}{h_{S,t}} \qquad (2.12) \\
HE_t &= \frac{2 * MVHR_t \sqrt{h_{S,t}}\sqrt{h_{F,t}} - MVHR_t^2 * h_{F,t}}{h_{S,t}}
\end{aligned}
$$

2.3.2.2 Constant Conditional Correlation (CCC) Model

In addition to the BEKK model, Kroner and Sultan (1993) combines the Error Correction Model (ECM) of the cointegration relationship with the GARCH model, proposes another way to set the multivariate GARCH model, and obtains the CCC-GARCH model.

$$
H_t = \begin{bmatrix} h_{S,t} & h_{SF,t} \\ h_{SF,t} & h_{F,t} \end{bmatrix} = \begin{bmatrix} \sqrt{h_{S,t}} & 0 \\ 0 & \sqrt{h_{F,t}} \end{bmatrix} \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \begin{bmatrix} \sqrt{h_{S,t}} & 0 \\ 0 & \sqrt{h_{F,t}} \end{bmatrix} = D_t R D_t \qquad (2.13)
$$

where ρ is the correlation coefficient between the spot market ratio of return and the futures market ratio of return. H_t is a 2×2 conditional covariance matrix, D_t is a 2×2 diagonal matrix composed of conditional standard deviations, and R is a 2×2 symmetric matrix.

The hedging ratio estimated using the CCC-GARCH model:

$$
\begin{aligned}
MVHR_t &= \frac{h_{SF,t}}{h_{F,t}} \\
HE_t &= \frac{h_{S,t} - (h_{S,t} + MVHR_t^2 * h_{F,t} - 2 * MVHR_t \sqrt{h_{S,t}}\sqrt{h_{F,t}})}{h_{S,t}} \qquad (2.12) \\
HE_t &= \frac{2 * MVHR_t \sqrt{h_{S,t}}\sqrt{h_{F,t}} - MVHR_t^2 * h_{F,t}}{h_{S,t}}
\end{aligned}
$$

2.3.2.3 Dynamic Conditional Correlation (DCC) Model

Although the CCC method is a multivariate time series model with time-varying conditional variance and covariance, the assumption of its invariant conditional correlation coefficient is not without criticism. Therefore, Engle (2002) extended this model and proposed a multivariate GARCH (DCC-MGARCH) model with Dynamic Conditional Correlation.

$$
\begin{aligned}
& r_t = \begin{bmatrix} RS_t \\ RF_t \end{bmatrix} \\
& r_t \mid \Omega_{t-1} \sim F(x_1, x_2 \mid \Omega_{t-1}) \\
& H_t = Var(r_t \mid \Omega_{t-1}) = D_t R D_t \\
& \varepsilon_t = D_t^{-1} r_t \\
& Q_t = \left(1 - \sum_{m=1}^{M} \alpha_m - \sum_{n=1}^{N} \beta_n\right)\overline{Q} + -\sum_{m=1}^{M} \alpha_m \left(\varepsilon_{t-m}\varepsilon_{t-m}^{'}\right) + \sum_{n=1}^{N} \beta_n Q_{t-n} \\
& R_t = Q_t^{*-1} Q_t Q_t^{*-1}
\end{aligned}
\tag{2.14}
$$

where RS_t and RF_t are the yield series of the spot and futures after the mean filtering, respectively, and their mean values are 0; D_t is a 2×2 diagonal matrix, two values on the diagonal in the matrix are the conditional standard deviations of the spot and futures yield series obtained by the univariate GARCH model; R_t is the time-varying correlation matrix; ε_t is the sequence of yields normalized by the conditional standard deviation; $\overline{Q}$ is the unconditional covariance matrix of the normalized ratio of return sequence; Q_t^* is the diagonal matrix obtained by the square root of the Q_t diagonal element. The hedging ratio estimated using the DCC-GARCH model is also the equation (2.14).

$$MVHR_t = \frac{h_{SF,t}}{h_{F,t}}$$

$$HE_t = \frac{h_{S,t} - (h_{S,t} + MVHR_t^2 * h_{F,t} - 2 * MVHR_t \sqrt{h_{S,t}} \sqrt{h_{F,t}})}{h_{S,t}} \qquad (2.12)$$

$$HE_t = \frac{2 * MVHR_t \sqrt{h_{S,t}} \sqrt{h_{F,t}} - MVHR_t^2 * h_{F,t}}{h_{S,t}}$$

In this chapter, we examine the hedging performance of the dynamic hedge ratios produced by the dynamic BEKK, CCC, as well as DCC models, and compare them with the hedging effectiveness for the constant hedge ratios generated from both OLS and VECM regression models. For comparison purpose, performance of the unhedged position and naive hedge ratio of one are also evaluated.

2.4: Data Descriptions and Empirical Results

2.4.1 Data Descriptions

The China Securities Index 300 (CSI 300), designed and managed by China Securities Index Co., Ltd., was launched on April 8, 2005. CSI 300 index is comprised of 300 stocks listed in Shanghai and Shenzhen stock exchanges, accounting for approximately 60% of market capitalization of both stock exchanges. Thus, it largely reflects Chinese A share market in terms of market scale, liquidity, and industry group. To provide investors with a tool to hedge risk in the stock market, CSI 300 stock index futures was launched on the China Financial Futures Exchange (CFFEX) on April 16, 2010. Details of the contract specifications of CSI 300 index futures are presented in Table 1.2 of Chapter 1. The detail information and the description of the dataset has been already given in Chapter 1.4

As discussed in the session above, stock market of China has experienced a sharp drop in the summer of 2015. In order to ease and mitigate the market fear, the government required China Financial Futures Exchange (CFFEX) to publish strict regulations on stock index futures trading on September 2nd, 2015. Due to strict regulations, the Chinese index futures transaction volume has dropped substantially, adversely affected the liquidity of the CSI300 index futures market. In this chapter, we divide the research data into two periods (01/01/2012 – 02/09/2015 and 03/09/2015-31/12/2018) to examine the CSI300 index futures' hedging effectiveness before and after the regulatory reforms in 2015.

As shown in Table 2.3, the returns of CSI300 index futures are not normally distributed. Only after the regulatory reforms, the skewness of IF2 is positive. In other cases, the skewness is negative. This shows that CSI300 stock index futures fell on most trading days. It also implies that the CSI300 stock index futures rose more evenly on the rising trading day. Meanwhile, no matter IF1 or IF2, the influence of skewness before and after the regulatory reforms is very large. Especially after the regulatory reforms, the skewness of IF1's return is negative, and the skewness of IF2's return is positive, which indicates that the return of the two contracts of CSI300 index futures is opposite.

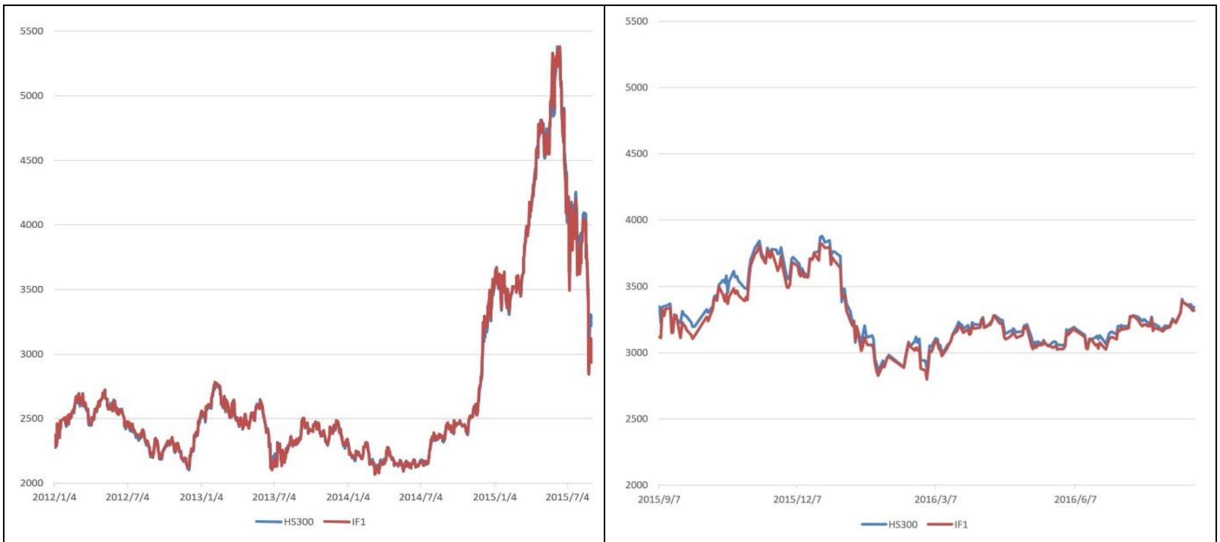
Table 2.3 Descriptive statistics of the returns of CSI300 index futures

		IF1			IF2		
		Before	After	Whole	Before	After	Whole
mean	5min	0.00053	0.00048	0.00059	0.00041	0.00071	0.00058
	60min	0.0058	0.0051	0.0059	0.0046	0.0086	0.0057
	daily	0.024	0.026	0.030	0.018	0.044	0.029
Std. Dev	5min	0.26	0.20	0.25	0.27	0.22	0.25
	60min	0.79	0.78	0.79	0.82	0.80	0.82
	daily	1.88	1.82	1.87	2.00	1.94	2.00
skewness	5min	-0.11	-0.91	-0.15	-0.36	0.11	-0.19
	60min	-0.22	-0.34	-0.24	-0.37	0.20	-0.26
	daily	-0.42	-0.24	-0.36	-0.20	0.046	-0.1386
kurtosis	5min	77.69	56.82	79.58	15376000	39.50	91.02
	60min	17.13	9.50	15.61	20.42	10.43	18.49
	daily	8.69	5.09	7.98	11.22	5.64	10.09
Jarque.Bera	5min	9.92e+6***	2.32 e+6***	1.511 e+6***	1.54 e+6***	1.065 e+6***	2.00 e+6***
	60min	37005***	2119.3***	37386***	56317***	2743.1***	56377***
	daily	1223.9***	45.30***	1186***	2506.6***	69.07***	2363.3***
Q(20)	5min	204.7***	88.19***	205.0***	172.7***	130.0***	191.3***
	60min	91.35***	26.50**	95.33***	122.1***	35.01**	130.9***
	daily	89.77***	20.85***	77.83***	91.30***	24.19*	73.07***
ADF	5min	-32.69***	-26.10***	-36.60***	-32.35***	-25.76***	-36.31***
	60min	-16.30***	-10.90***	-17.53***	-16.69***	-11.01***	-17.99***
	daily	-8.03***	-5.45***	-10.57***	-7.94***	-5.74***	-10.39***

The list of statistic description for the return of IF1 and IF2, including mean, std, skewness, etc. Before represents 01/01/2012 – 02/09/2015; After represents 03/09/2015-31/12/2018; and Whole represents 01/01/2012 -31/12/2018. *, **, and *** indicate 10%, 5%, 1% significance, respectively. $\mathrm{RF_t} = 100 * (\mathrm{IF_t} - \mathrm{IF_{t-1}})$ $\mathrm{IF_t} = \ln(\mathrm{futureprice})_t$ "IF1","IF2" means Index Futures price of 1 and 2-month maturity.

In this chapter, the futures and index data are equally segmented at 5min, 60min, and daily with the trading price at the first time point of each segment are analyzed. If there is no transaction at this moment, the latest transaction data was selected as an alternative.

Figure 2.1 CSI300 Index Price and Futures Prices at 1 month before maturity



Before (01/01/2012 – 02/09/2015)	After (03/09/2015-31/12/2018)

The CSI300 Index weekly price during 01/01/2012 – 02/09/2015 (left panel, defined as before) and 03/09/2015-31/12/2018 (right panel, defined as after). Before represents 01/01/2012 – 02/09/2015; After represents 03/09/2015-31/12/2018.

2.4.2 Empirical Results

As discussed, more and more studies have begun to use high-frequency data in analyzing the efficiency and impact of stock index futures markets. In particular, for the study of hedging effectiveness, it is believed that high-frequency data can provide a more detailed insight and information. Hourly data or minute data allow one to examine the unique intraday pattern and features, and research that based on high frequency data is considered to be able to respond quickly to financial market information. For instance, for our sample period (2012-2018), the daily data has only 1129 observations but there are 98034 items if data at 5-minute level were employed. For the same analytical model, intraday data offers a larger sample and contain more information that can help one to understand the functioning and dynamics of index futures markets.

2.4.2.1 Unit Root Test and Cointegration Test

Unit Root Test

Cointegration of two price series is a necessary condition for market efficiency, since the market efficiency hypothesis implies that the future price is an unbiased predictor of the future spot price. If the two series are cointegrated, spot price and futures price move together and will not tend to drift apart over time. According to Brenner and Kroner (1995), if the net cost of carry has a unit root, then cash and futures prices will tend to drift apart, and they would not be cointegrated. On the contrary, if the differential is stationary, then spot and futures prices are tied together, and they would be cointegrated.

Table 2.4 Unit Root Test of returns of index futures before and after Regulatory Reforms

		Return of IF1			Return of IF2		
		BEFORE	AFTER	WHOLE	BEFORE	AFTER	WHOLE
ADF	5min	-66.14***	-42.41***	-79.53***	-66.45***	-42.29***	-79.77***
	60min	-20.36***	-11.25***	-23.06***	-20.75***	-11.24***	-23.29***
	daily	-8.04***	-4.22***	-10.36***	-7.96***	-4.24***	-10.24***
DFGLS	5min	-26.70***	-3.09***	-30.42***	-35.30***	-3.27***	-40.44***
	60min	-18.72***	-1.71*	-21.86***	-20.05***	-1.48***	-23.38***
	daily	-2.91***	-6.93***	-3.28***	-3.13***	-7.57***	-3.56***
PP	5min	-42409***	-19228***	-61500***	-42798***	-19710***	-62338***
	60min	-4982***	-1144***	-6105***	-4948***	-1181***	-6112***
	daily	-826.3***	-244.6***	-1089***	-783.3***	-240.1***	-1035***
KPSS	5min	0.14	0.053**	0.078	0.14	0.059	0.074
	60min	0.12	0.096	0.084	0.12	0.10	0.078
	daily	0.12	0.099	0.080	0.12	0.10	0.075

The list of unit root test of returns for the IF1 and IF2. Thereinto, ADF = augmented Dickey–Fuller; DFGLS= the modified Dickey–Fuller test by transforming time-series data via a generalized least squares regression; PP = Phillips–Perron; KPSS =Kwiatkowski–Phillips–Schmidt–Shin. *, **, and ***mean 10%, 5%, 1% significance, respectively. The definitions of before, after and whole are as same as in Table 2.3.IFn means Index Futures price of 1 or 2-month maturity, St means Index price(spot).

As we discussed above, using intraday data at 5-min, 60-min level and daily data of spot (index) and futures price, the results from unit root tests shows that a unit root for spot price (index) and futures price of both maturities (1m and 2m) cannot be rejected at 5% significant level in the ADF, the DF-GLS, and the PP tests. Similarly, the null hypotheses of stationarity are rejected at 5% significant level by the KPSS test. The implication is that the spots and futures price are nonstationary. Nevertheless, first differences of spot price (index) and futures price are stationary. The ADF, DF-GLS, and PP tests all rejected a unit root hypothesis at 1% significant level. Likewise, KPSS test does not reject a stationary null hypothesis. It means the first differences of spot price and futures price do not have a unit root, and they are stationary.

In related articles, Tharavanij (2017) and Kenourgios (2005) investigate whether the existence of stock index futures has increased positive feedback trading in emerging market, Thai stock index futures (SET50 futures) and Athens stock index futures (ASE-20 futures). To determine the order of each price series, the Augmented Dickey-Fuller test and Phillips-Perron test are computed on the levels of each price series. The same with Thai stock index futures (SET50 futures), CSI300 index futures shows consistent performance in both ADF and PP tests, significantly rejecting the null hypothesis which series is non-stationary. However, CSI300 index futures only reject the null hypothesis at the level of 10% in the DF-GLS test. Correspondingly, the SET50 can reject at the level of 1%. The results show that both CSI300 index futures and SET50 index futures in Asia emerging markets, their first difference and basis of spot price and futures price are stationary.

According to Kenourgios (2005), performing the tests on the levels of each series in Greek futures show that the null hypothesis of a unit root is not rejected. Which means the emerging Greek futures market is inefficiency. The PP test tends to be more robust to a wide range of serial correlations and time-dependent heteroskedasticity. The asymptotic distribution of the PP t-statistic is the same as the ADF t-statistic. After comparing CSI300 and ASE-20 index futures, we can find the first difference and basis of spot and futures price of CSI300 show consistent performance in both ADF and PP tests, at 1% level significantly rejecting the null hypothesis which series is non-stationary. While the ASE-20 futures could not reject the null hypothesis in 5% level. The empirical results presented in this session suggest that the ASE-20 futures market is inefficient, and futures prices appear not to be unbiased predictors of spot prices for one month prior to maturity of the futures contract. This finding has an important implication for market participants in the Greek capital market, indicating that there are more opportunities for possible speculative profits to be made in Greek futures market than in Chinese futures market.

Antoniou and Holmes (1996) investigate the FTSE-100 stock index futures market, which is one of the most mature markets. Results show that the FTSE-100 index futures market is efficient and provides an unbiased estimate of futures' spot prices for one and two months away from expiration. In this session, after performing the augmented Dickey–Fuller (ADF) test, the modified Dickey–Fuller test by transforming time-series data via a generalized least squares regression (DF-GLS) test, Phillips–Perron (PP) test, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, the unit root test of CSI300 index futures showed that the series of one and two months away from expiration contracts are stationary.

The implication is that in the unit root test, CSI300 index futures performance is already equivalent to a mature market.

Cointegration Test

Cointegration of two price series is a necessary condition for market efficiency, since the market efficiency hypothesis implies that the future price is an unbiased predictor of the future spot price. If the two series are cointegrated, spot price and futures price move together and will not tend to drift apart over time. If this is the case then the futures price is an unbiased predictor of the future spot price. In order to test for cointegration between the two markets, the Johansen Maximum Likelihood Procedure (Johansen, 1988 and 1991) is implemented.

Table 2.5 Johansen's cointegration Test between CSI300 index and index futures price

		Trace statistic Rank=0			critical value		Trace statistic Rank<=1			critical value	
		Before	After	Whole	5%	1%	Before	After	Whole	5%	1%
IF1	5min	114.26***	102.94***	242.46***	15.67	20.20	1.38	4.66	2.06	9.24	12.97

	60min	62.39***	53.62***	105.73***	15.67	20.20	1.34	3.36	1.85	9.24	12.97
	daily	20.63***	40.44***	75.04***	15.67	20.20	1.81	2.77	2.22	9.24	12.97
IF2	5min	27.95***	52.81***	82.89***	15.67	20.20	1.70	4.77	2.13	9.24	12.97
	60min	22.87***	33.45***	43.54***	15.67	20.20	1.50	3.43	1.91	9.24	12.97
	daily	11.49	28.57***	41.04***	15.67	20.20	1.86	2.65	2.16	9.24	12.97

Johansen's cointegration Test between CSI300 index and IF1, IF2 price. The trace test is used to test the null hypothesis that the number of cointegrating vectors is less than or equal to rank, where rank=0 (for no cointegration) or 1 (for a single cointegration vector). The definitions of before, after and whole are as same as in Table 2.3.

Meanwhile, the futures price of 1-month and 2-months maturity are tested separately with the CSI300 index price (spot). The number of cointegrating vectors is less than or equal to the rank, where rank is either 0 (for no cointegration) or 1 (for a single cointegrating vector). The results from the Johansen's cointegration test shows that statistic results reject the null hypothesis of no cointegration between spot and futures prices. However, it could not reject the null hypothesis of a maximum of one cointegrating vector. If the null of both rank = 0 and rank = 1 are rejected, it would imply that both variables are stationary.

Tharavanij (2017) studies the cointegration of SET50 futures, using Johansen's cointegration test. The test statistic clearly rejects the null hypothesis of no cointegration between spot and futures prices. However, it could not reject the null hypothesis of a maximum of one cointegrating vector. The results are very similar with Johansen's cointegration test of CSI300 futures, no matter how regulatory reforms. This implies that futures price and subsequent spot prices at least move together overtime and will not drift apart indefinitely. This is consistent with the implications of market efficiency and unbiasedness hypothesis.

The evidence presented in Kenourgios (2005) implies that in Greek ASE-20 stock index futures market, the null hypothesis of zero cointegrating vectors is rejected at the 5% level, while the null of one cointegrating vector cannot be rejected. Spot price and futures price series are cointegrated, and then the first necessary condition for market efficiency is met. However, the second necessary condition for market efficiency does not hold, since the restrictions on the parameters α and b in the cointegrating relationship (α=0 and b=1) are rejected, even though the serial independence of et is accepted. Thus, the joint hypothesis of market efficiency and unbiasedness in futures prices is rejected, since both necessary conditions for market efficiency are not met, even though spot price and futures price series cointegrate. Moreover, this evidence is consistent with the findings of earlier studies on other European emerging futures markets (e.g., Martikainen et. al, 1995; Bühler and Kempf, 1995), supporting the inefficiency in those markets. Compared with Athens Stock Exchange (ASE), CFFEX plays an important role in the development of stock index futures.

Antoniou and Holmes (1996) investigate the FTSE-100 stock index futures market, which is one of the most mature markets. The results show that in all cases the null hypothesis of zero cointegrating vectors is rejected at 5% level, while the null of one cointegrating vector cannot be rejected. That for 1, 2 months prior to maturity the restrictions hold at the 5% level of significance. Thus, spot price and futures price series cointegrate, and the market efficiency and risk neutrality are accepted.

These results imply that, the CSI300 index futures market is efficient in

Johansen's test, and spot price and futures price series cointegrate.

2.4.2.2 Model Estimation Results

In order to evaluate the hedging efficiency of CSI300 index futures, a total of five estimation methods (i.e., OLS, VECM, VECM-BEKK, VECM-CCC, VECM-DCC) are employed in this chapter.

Table 2.6 Hedge ratio and hedging effectiveness of the CSI300 index futures (IF1)

		t	Before		After		Whole	
			MVHR	HE	MVHR	HE	MVHR	HE
Static Models	OLS	5min	0.71(0.83)	0.37(0.83)	0.67(0.72)	0.28(0.73)	0.70(0.78)	0.34(0.77)
		60min	0.84(0.87)	0.66(0.85)	0.80(0.81)	0.55(0.81)	0.83(0.84)	0.64(0.83)
		daily	0.88(0.89)	0.76(0.88)	0.88(0.88)	0.69(0.87)	0.88(0.88)	0.74(0.88)
	VECM	5min	0.71(0.85)	0.39(0.85)	0.68(0.74)	0.32(0.76)	0.70(0.79)	0.36(0.80)
		60min	0.85(0.89)	0.68(0.87)	0.81(0.82)	0.58(0.84)	0.84(0.85)	0.66(0.85)
		daily	0.90(0.91)	0.80(0.92)	0.89(0.89)	0.74(0.85)	0.89(0.90)	0.77(0.88)
Dynamic Models	VECM-BEKK-MVGARCH	5min	0.75(0.87)	0.45(0.83)	0.67(0.79)	0.33(0.75)	0.71(0.83)	0.40(0.79)
		60min	0.89(0.88)	0.75(0.88)	0.80(0.81)	0.58(0.79)	0.87(0.84)	0.72(0.83)
		daily	0.94(0.92)	0.86(0.89)	0.95(0.91)	0.82(0.87)	0.93(0.90)	0.84(0.88)
	VECM-CCC-MVGARCH	5min	0.75(0.87)	0.44(0.81)	0.65(0.78)	0.24(0.76)	0.72(0.82)	0.38(0.78)
		60min	0.90(0.86)	0.76(0.87)	0.79(0.83)	0.55(0.81)	0.87(0.85)	0.72(0.84)
		daily	0.94(0.91)	0.86(0.91)	0.89(0.93)	0.73(0.87)	0.92(0.92)	0.83(0.89)
	VECM-DCC-MVGARCH	5min	0.76(0.88)	0.45(0.86)	0.64(0.77)	0.20(0.73)	0.72(0.16)	0.38(0.79)
		60min	0.90(0.90)	0.77(0.88)	0.81(0.81)	0.57(0.80)	0.87(0.85)	0.72(0.85)
		daily	0.93(0.91)	0.85(0.93)	0.90(0.92)	0.75(0.85)	0.93(0.91)	0.84(0.90)

The list of hedge ratio and hedging effectiveness for IF1. MVHR is minimum-variance hedge ratio, which is the average value hedge ratio in dynamic model; HE is the hedging effectiveness; the R2 which represent for the goodness of fit of static model are given in parentheses. The definitions of before, after and whole are as same as in Table 2.3.

Table 2.7 Hedge ratio and hedging effectiveness of the CSI300 index futures (IF2)

		t	Before		After		Whole	
			MVHR	HE	MVHR	HE	MVHR	HE
Static Models	OLS	5min	0.71(0.78)	0.39(0.74)	0.62(0.72)	0.21(0.70)	0.69(0.76)	0.34(0.72)
		60min	0.81(0.83)	0.61(0.80)	0.79(0.79)	0.55(0.78)	0.80(0.80)	0.60(0.79)
		daily	0.82(0.88)	0.67(0.86)	0.82(0.87)	0.63(0.85)	0.82(0.87)	0.66(0.85)
	VECM	5min	0.71(0.79)	0.41(0.76)	0.65(0.73)	0.27(0.71)	0.69(0.77)	0.36(0.74)
		60min	0.81(0.85)	0.63(0.85)	0.79(0.83)	0.57(0.81)	0.81(0.84)	0.61(0.83)
		daily	0.83(0.91)	0.70(0.87)	0.86(0.88)	0.70(0.87)	0.83(0.90)	0.68(0.87)
Dynamic Models	VECM-BEKK-MVGARCH	5min	0.75(0.81)	0.47(0.80)	0.63(0.76)	0.25(0.75)	0.72(0.79)	0.41(0.77)
		60min	0.89(0.87)	0.75(0.86)	0.78(0.83)	0.58(0.81)	0.87(0.85)	0.71(0.83)
		daily	0.92(0.93)	0.83(0.90)	0.84(0.91)	0.76(0.89)	0.91(0.92)	0.81(0.90)
	VECM-CCC-MVGARCH	5min	0.77(0.84)	0.49(0.81)	0.63(0.79)	0.21(0.76)	0.73(0.82)	0.40(0.79)
		60min	0.89(0.89)	0.75(0.87)	0.79(0.81)	0.57(0.79)	0.87(0.85)	0.71(0.84)
		daily	0.91(0.91)	0.82(0.90)	0.87(0.89)	0.71(0.88)	0.90(0.90)	0.80(0.89)
	VECM-DCC-MVGARCH	5min	0.77(0.85)	0.48(0.81)	0.64(0.82)	0.21(0.79)	0.73(0.83)	0.40(0.80)
		60min	0.90(0.88)	0.76(0.86)	0.79(0.86)	0.57(0.83)	0.87(0.87)	0.71(0.84)
		daily	0.91(0.91)	0.83(0.89)	0.82(0.90)	0.60(0.88)	0.90(0.90)	0.80(0.88)

The list of hedge ratio and hedging effectiveness for IF2. The definitions of before, after and whole and other parameters are as same as in Table 2.3.

Because the risk ratio of OLS can be regarded as the average or unconditional risk ratio (lien 2009), the OLS can be benchmarked. Table 2.6 and 2.7 show the results of the hedging effectiveness of CSI300 index futures as given by various models. The following observations can be made from these two result tables.

First, based on the daily hedging performance, the CSI300 index futures' hedging effectiveness of static and dynamic models is ranging from 73% to 85%, indicating that CSI300 index futures can provide investors an effective tool in hedging underlying stock mark risk. However, as discussed before, the Chinese regulatory authorities tightened regulations on stock index futures trading on September 2, 2015. The empirical results from almost all of models show the hedging effectiveness drop significantly after that. This result is different to Wei (2018), who shows that the hedging effectiveness of CSI300 index futures did not changed significantly after 2015. Regulations reforms lead to the decrease trading activities and volume, and this limited participation in stock index futures will likely reduce the effectiveness of index futures as a hedging tool during the turbulent period.

Second, all CSI300 futures contracts with maturity terms show that the hedging strategies derived from dynamic models could offer a higher risk reduction. The best hedging effectiveness is based on the daily data, and the performance of dynamic models (Average HE = 83%) is better than that of static models (Average HE = 76%). For the current month contract (IF1), the DCC-MVGARCH model (HE=84% in daily data) performed slightly better. For the next month contract (IF2), the BEKK-MVGARCH model (HE=81% in daily data) performed better. These results are similar with Myers (1991), Kroner & Sultan (1993), Park & Switzer (1995). They show that dynamic hedge ratios outperform constant hedge ratios in terms of reducing the portfolio risk, and dynamic hedging significantly improves the effectiveness (as the hedge ratios are updated with the arrival of new information into the market).

Third, there is no significant difference in both hedging ratio and hedging effectiveness of the static OLS (HE=74% in daily data) and VECM models (HE=77% in daily data). Similarly, Lien (2002) find that VECM-BGARCH model fails to significantly outperform the unconditional hedge ratios estimated from OLS, ECM, and RCM methods in terms of VR. This is particularly true for the hedge ratios of the commodity futures, and when compared to OLS hedge or even the naive hedge. Thus, OLS model appears to a good candidate for the static hedge.

Fourth, with regards to the relationship between hedging ratio, the hedging effectiveness, and the maturity of the futures contract, the results show that as the contract expiration period get longer, the hedging ratio (MVHR) is gradually decreasing, and the hedging effectiveness (HE) is gradually reducing. The traditional futures hedging theory suggests that the nearby contract transactions should be more active than the far contracts, and as they have the ability to better reflect the spot price fluctuation characteristics, the higher the hedging effectiveness should be. The performance of CSI300 stock index futures is consistent with traditional theory.

Fifth, the hedging effectiveness (HE) increases as the frequency of data decreases. The performance of 5-min level data is worse than the data of 60-min level in every model. Liang (2009) points out that most individual investors in CSI300 index futures traded intraday, which also affected high frequency intraday hedging effectiveness. Unlike the 5-min and 60-min level data, daily-level hedging effectiveness is the best, indicating that the CSI300 stock index futures are effective hedging instruments. Sim and Zurbruegg (2001), illustrates that changing positions too frequently will increase transaction costs and will not improve the hedging effectiveness. Simpler and less frequently updated dynamic hedging strategies, like the rolling-window hedge, could still be preferable. Further, if we consider the difficulty of managing frequent transactions and the transaction costs (much more higher in CSI300 market compared to others), the hedging efficiency will be further deteriorated. These results suggest that futures traders should not perform the high frequency hedging transactions in the

CSI300 index futures market, which is in line with previous studies (Qu, et al 2019 and Chen and Gong, 2019).

Our results are different to the findings of Wei (2013) on CSI300 index futures hedging effectiveness. Wei (2013) shows that, static model has the higher hedging effectiveness, the OLS and VECM models did not show a significant difference, and with the contract expiration period getting longer, the hedging effectiveness increases. The reason might be that Wei (2013) use the data at 15-min level in 2010-2011, the initial year of CSI300 index futures, most investors are not familiar with derivatives rules. Most of them are speculators than institutional hedgers. The nearby contract has large volume of transactions and good liquidity, attract speculators to participate in. Meanwhile, institutional hedgers need longer holding periods and prefer long-term contracts. Both of them result in the nearby month futures prices deviating from spot prices.

Finally, it should be pointed out that CSI300 stock index futures have a relatively low hedging effectiveness compared to other index futures contracts. Our results show that hedging effectiveness of CSI300 index futures is only about 85%. However, Kenourgios (2008) shows that, in US market, S&P500 stock index futures can provide up to 97% hedging effectiveness for the spot index. Laws (2005) document that the London International Financial Futures Exchange (LIFFE) FTSE100 and FTSE250 stock index futures contracts can provide 87% to 98% hedging effectiveness. In the Asian market, Wang, Hsu (2010) reveal that the Nikkei 225, HSI and KOSPI 200 index contracts all have more than 90% hedging effectiveness. Emerging Malaysian

KLSE stock index futures, on the other hand, can provide 75% to 80% hedging effectiveness (similar to that of CSI300 stock index futures). Two possible reasons are accounted for the lower effectiveness. First of all, China CSI300 stock index futures market is relatively new, the trading volume of futures index has still relatively small compared with the size of the spot market, its price formation mechanism is not fully developed, and the price discovery ability is not clearly evident. Besides, the 2015 policy implementation further decreases the liquidity in turn narrow down the effectiveness correspondingly. Nevertheless, it is believed that the hedging effectiveness of CSI300 stock index futures can be significantly improved as the futures market becomes more active and mature.

2.5: Conclusions

2.5.1 Introduction

When using stock index futures for hedging, the important issue for hedgers is how to calculate minimum variance hedge ratio (MVHR) to reduce the risk of spot volatility (variance). MVHR is defined as the ratio of the number of futures to the number of spots in the hedging operation. Clearly, using different hedge ratios will reduce spot risk (variance) to varying degrees. In order to measure the degree of risk reduction by various hedging methods and hedging ratios, a measure of hedging effectiveness based on MVHR is proposed.

In this chapter we examine the extent to which CSI300 stock index futures can provide investors an effective tool to hedge for the spot index risks. In addition, we have also investigated the question of whether the hedging effectiveness of CSI300 index futures contracts is dependent on contract maturities and different time period.

Taken together, this chapter adds to the existing literature in the following ways. Firstly, in order to investigate the hedging effectiveness in high frequency environment, the 5-min and 60-min data are compared with the daily data. Secondly, for the first time, we compare the hedging effectiveness of CSI300 stock index futures before and after regulation reforms. Thirdly, the futures contracts of both the current and next month are examined to evaluate the hedging effectiveness of these two types of futures contracts. Finally, from the methodological point of view, several static and dynamic models are analyzed and compared in terms of their hedging effectiveness.

2.5.2 Summary of Findings

This chapter first conducts an empirical analysis of the intraday hedging effectiveness of CSI300 stock index futures. Through the use of multiple hedging models, the static and dynamic hedging ratios and effectiveness in two maturity contracts are studied. The main empirical results can be summarized as follows. Firstly, under the high-frequency hedging environment, compared with other mature stock index futures markets, CSI300 stock index futures have a relatively lower hedging effectiveness (only around 85%). And the daily data shows a better hedging effectiveness than high frequency data. Secondly, after the regulations reforms, the hedging effectiveness decrease rapidly. Thirdly, the dynamic hedging model such as MVGARCH can achieve a better hedging effectiveness than their static counterpart. Finally, the static

OLS and VECM models does not show any significant difference in their hedging effectiveness.

2.5.3 Policy Implications

According to our empirical results, the hedging effectiveness of CSI300 index futures decrease rapidly after the regulations reforms in 2015. In addition, compared with other mature markets, CSI300 stock index futures still has a weaker price discovery ability and a lower hedging effectiveness. In order to enhance the price discovery ability of CSI300 stock index futures and to improve the hedging effectiveness, regulators in China should gradually relax restrictions on investors' participation in stock index futures trading.

Firstly, the market regulators could reduce transaction fees. According to our empirical results, the hedging effectiveness of high frequency hedge is significantly lower than that of daily data. This shows that institutional investors are difficult to achieve classic hedging within the day. Reducing fees help investors cut hedging costs, which in turn may enhance their hedging effectiveness especially in short time periods.

Secondly, margin should also be adjusted back to the level before the reforms in 2015. The current margin is too high to achieve an effective hedging transaction. Margin plus backup funds currently account for 40-50% of the underlying spot, affecting the enthusiasm of both individual and institutional investors.

Thirdly, it has been argued that the trading lot limit should be abolished. Each account can only trade 20 lots per day, which can only hedge nearly RMB 20 million yuan in spot positions. The hedging needs of large institutional investors simply cannot be met in such a restrictive trading environment.

2.5.4 Suggestions for Further Research

In this chapter, only the historical in-sample hedge ratios are estimated to examine the hedging effectiveness of index futures market in China. Other way to evaluate the effectiveness of alternative hedging strategies is using the out-of-sample framework.

In our empirical investigations this chapter employs various frequency of data, different contract of maturity, several static and dynamic models, and different time periods before and after regulatory reforms. Further research could pay more attention on the relationship between hedging horizons and optimal hedging strategies.

We found that static models (OLS and VECM) tend to have similar hedging effectiveness. Therefore, considering issues such as management difficulty and cost, static strategies could also be a good candidate for hedging the CSI300 stock index. This chapter however does not explicitly consider the management cost and difficulty involved in high frequency trading. Especially for dynamic models, how to choose the appropriate trading frequency will directly affect the performance of a hedging strategy.

One of the limitations of GARCH models is that they are incapable of reliably capturing the patterns of financial data series, specifically the asymmetric impact of news (Engle & Ng, 1993; Glosten et al., 1993; Kroner & Ng, 1998). Negative shocks are widely known to have a greater impact on financial series than positive shocks. This fact should be taken into account when the hedge ratios are estimated. Brooks et al. (2002) conclude that hedging effectiveness is greater when this asymmetric behavior is considered. A further limitation of GARCH models is that they consider high-volatility persistence.

Finally, in this chapter we employ the performance measures based on the Risk Minimization principle. However, as discussed, adopting the MVHR hedging strategy may have to sacrifice a certain level returns at the same time. In the future, we aim to extend to the current research from the perspective of complex dynamic models and market state transition, and to examine other performance measures based on the Portfolio Approach in order to directly consider the risk-return relationship. This in turn requires a better understanding of price discovery capabilities of CSI300 stock index futures, which is the main research focus in the next chapter.

Chapter 3 - Price Discovery in CSI300 Index Futures Market

3.1: Introduction

3.1.1 Research Background

Whether price reflects the fundamental value of a security is one of the fundamental questions in finance. This question is of great interest to academics, policy makers, as well as practitioners. In well-functioning and efficient financial markets, the price of a security reflects its fundamental value. This is because, in these markets, any new information that affects the fundamental value of the security is rapidly captured in the price. However, the new information would not be instantaneously impounded into the price due to the existence of market imperfections like transaction costs, information asymmetry, regulations, etc. For example, an investor with private information may split its total trade into many smaller trades in order to maximize her profit. This will lead to a situation whereby the price reflects the new information in a gradual fashion.

Indeed, different market structures uniquely affect the processing of incoming information. Each particular security design is distinguished from other designs by the speed at which it digests new information. Garbade and Silber (1979) put forward the terminology of “dominant” and “satellite” markets. Dominant markets lead satellite markets; that is, they are more influential in the price discovery process. Satellite markets rely on dominant markets as the primary source of information. The leverage hypothesis states that market that offer a higher leverage opportunity should provide a better price discovery. Kawaller et al. (1987) investigate the intraday price relationship between S&P 500 futures and the index. They suggest that the leverage effect is one of the primary reasons that informed traders choose to trade in the futures market. The trading cost hypothesis predicts that the security incurring the lowest trading cost attracts informed trading. Trading costs include commissions and bid-ask spreads. Because profit is reduced by trading costs, informed traders have an incentive to trade in the market with the lowest trading cost. As Lau and McInish (1995) point out, any information that changes equilibrium value on a scale different from the minimum tick size will not be correctly reflected in the price. Market-wide information hypothesis predicts that futures serve a more significant price discovery function than the spot index market. Boot and Thakor (1993) show that index derivatives should enhance the processing of market-wide information. The significance of the price discovery role of an index instrument depends on whether the design of security allows traders to disseminate and act on market-wide information efficiently. If the price discovery depends on transaction costs, as suggested by Fleming, Ostdiek, and Whaley (1996), then one can expect the price discovery to take place in the futures market instead of spot market due to low transaction cost associated with futures trading. Alternatively, price discovery may depend on the relative number of participants in each market as shown in the theoretical model suggested by Garbade and Silber (1983).

A similar situation is encountered when dealing with securities that have derivatives. One can take a long position in an underlying security by buying the underlying security itself or by taking positions in derivative securities like futures and options. In this case, one would like to know whether the price discovery takes place in the security (spot) market or the derivatives (futures) market. This brings one to the question of how the price discovery is measured. So and Tse (2004) shows that three major approaches of studying the price discovery of assets have been identified. The first approach focuses on the lead-lag relationship between the prices of national markets, or between different securities. The second approach involves examination of the role of volatility in the price discovery process. The third approach attracts a great attention from academia in the study of how information is transmitted among different markets. Using the common factor (or implicit efficient price) among cointegrated prices, information sharing techniques, Permanent Temporary model (Gonzalo and Granger, 1995), Information Share model (Hasbrouck, 1995) and Modified Information Share model (Lien and Shrestha 2009) have been used to study the contribution of price discovery from closely related markets.

A number of studies have empirically investigated the issue of price discovery between stock index futures and stock index markets. These studies mainly focus on the price lead-lag relationship between stock index futures and stock index, and information share. Herbst et al. (1987), Chan (1992), Martens et al. (1998) examined the price transfer between the S&P500 index and the index futures market. Their results show that futures price changes are 5 to 45 minutes ahead of spot price changes. Abhyankar (1995) employed the EGARCH model to study the lead-lag relationship in the FTSE100 index and the S&P500 index markets using the 5-minute level data in 1992. It was found that the futures prices of both indices are ahead of the spot price, leading 15 to 20 minutes. Lihara et al. (1996) studied the relationship between the Japanese stock index and the futures market, and found that the futures return is ahead of the spot time of up to 20 minutes, while the spot return is only up to 5 minutes ahead of the futures return. The lead-lag relationship between the spot and futures markets can be explained by the lower transaction costs of the futures market, the absence of short selling restrictions and higher leverage.

Kim et al. (1999) applied the vector autoregressive (VAR) model to test the futures and spot relationships of the S&P500, MMI and NYSE composite indices. They found that S&P500 leads in the futures market, while the spot market is dominated by the MMI index. Ryo and Smith (2004) studied the lead-lag relationship between the Korean futures market and the securities spot market, and the results were similar to most studies in other markets. Using the bivariate GARCH model and 5-minute level intraday data, Chan et al. (1991) show that the volatility of S&P500 spot and futures market returns are transitive and mutually predictable. Booth et al. (1996) used the daily closing price of the Nikkei 225 Index futures contract from 1990 to 1994 to study the information transfer mechanism in the Osaka Stock Exchange, the Singapore Exchange and the Chicago Stock Exchange. It is found that none of market above can be confirmed as the main source of information flow. Tse (1999) examined the price discovery of the Dow Jones Industrial Average (DJIA) spot and futures and found that the futures market dominated the price discovery. Booth et al. (1999) analyzed the spot, futures and options markets of the German DAX index and found that the spot and futures markets shared equally the role of price discovery, while the options market did not play any significant role. Chu et al. (1999) studied the price discovery between the S&P500 index, S&P500 futures and the S&P500 depository receipt market. The results show that the futures market is the main source of information, followed by the S&P500 depository certificate market, S&P500 index market contributes least to the process. Covring et al. (2004) examined the price discovery process in the Nikkei 225 index on the Tokyo Stock Exchange, the Osaka Stock Exchange and the Singapore Exchange. The results show that the information contribution ratio of the Nikkei 225 spot market is 23%, 44 % for Osaka Futures Market, and the Singapore futures market is 33%. Their results show that the index and the index futures market interact with each other, but the futures market is more sensitive to the information on the market, usually ahead of the spot market, and the futures market is dominant in price discovery.

3.1.2 Research Aims and Objectives

Economic developments in China during the past 20 years have been spectacular. With a population of over 1.4 billion people, China has always been regarded as a market with huge potential and the foreign direct investment in China has increased significantly in recent years. Paralleling China's economic development, the Chinese financial market has also played a crucial role in channeling this increasing amount of investment capital. Therefore, an understanding of the functioning and efficiency of Chinese financial markets (including its stock index futures markets) is important to the international investor's understanding of China's business.

According to the trading cost hypothesis, futures is likely to reflect information quicker than the spot market due to its lower transaction costs. Unlike other stock market indexes, the CSI300 Index is skewed towards a few big firms with large weights in the index. This feature makes replicating the index in a portfolio of trades relatively easier and a handful of spot market trades can effectively track the index movement. Hence, it is interesting and informative to investigate the price discovery process in the CSI300 index market and to provide additional insight on the trading cost hypothesis.

On April 16, 2010, CSI300 stock index futures were launched. Hua (2010) argue that the Chinese stock index futures market is likely to play an important role in price discovery process and will be conducive to the stability of the capital market. However, there are also concerns that the Chinese stock index futures market has excessive speculation and insufficient price discovery capabilities. Until now, does the CSI300 index futures market has a price discovery function? Which market is in a dominant position between the stock index futures market and the stock index market? What is the information share contribution of CSI300 futures market in price discovery? These issues are not fully understood. Our investigation of the issues identified above can not only reveal the price discovery ability of the Chinese stock index futures market, but also provide valuable information to market participants and regulatory authorities. A better understanding the microstructure and price discovery mechanism of the Chinese stock index futures market also has important theoretical and practical significance.

Therefore, this chapter focuses mainly on addressing the following questions regarding the price discovery function of Chinese index futures market.

- Whether the CSI300 stock index futures market plays a significant role in price discovery? Compared with other more mature index futures markets, what is the relative contribution of CSI300 futures market?
- Which market is dominant in the information transmission, between CSI300 index and CSI300 index futures markets?
- Whether the price discovery capabilities of CSI300 index futures market vary across different frequency of data?

For the Chinese stock index futures market, most of the existing research focuses on the relationship between the CSI300 index futures simulation trading market and the CSI 300 index. For example, Yan et al. (2009) used the vector error correction model, the common factor model, and the bivariate EGARCH model with error correction to study CSI300 index simulation from October 30, 2006 to March 20, 2009 daily data. The price discovery effects between the CSI300 index futures market and the CSI300 index market show that the spot market plays a leading role in price discovery. Xing and Zhang (2010) studied the linkage between CSI300 index simulation futures and CSI300 index, and found that the introduction of stock index futures did not have much impact on the volatility of the underlying spot market, but increased the asymmetric effect of the stock market. Nevertheless, during the simulation trading and real trading, the psychology and expectation of spot and index futures investors may be different, which will inevitably affect the price behavior of the simulation market and the real market. Thus, the empirical analysis based on the simulated transaction data rather than the real transaction data could be biased and problematic. As the Chinese real stock index futures market has just become fully operational in 2010, the empirical research on the information transfer relationship between CSI300 spot and index futures markets and their relative price discovery contribution is still very limited. This paper therefore aims to fill in this gap of the literature.

3.1.3 Research Significance

This chapter contributes to the existing literature in a number of ways. First, this study adds to the extensive literature that investigates information share of financial markets by examining a relatively new index futures market in China with several widely used measures of price discovery (PT/GG, IS and MIS methods). Second, to the best of our knowledge, this chapter is also the first empirical investigation of the impact of regulatory reforms on the CSI300 index futures price discovery role. Third, we have also empirically estimated and compared the price discovery of CSI300 index with that of other major futures contracts on S&P 500, Tokyo Stock Price Index (TOPIX), and Financial Times Stock Exchange (FTSE) 100 index. Finally, this study employs both daily and intraday data (at 5min and 60min level) to examine if the price discovery ability varies with data frequency and contract maturity, in order to determine whether the market is microscopically effective. Overall, the results of this chapter on price discovery could help market regulators and participants to formulate more effective strategies.

Our results show that CSI300 Index Futures market contributes to discovery of information and the spot market does not play a significant role in the information revelation process. Findings confirms that CSI300 index futures and spot markets are informationally linked, and information is being transmitted from one market to another.

3.1.4 Roadmap

The remainder of the chapter is divided into four sections. In Session 2, the developments of price discovery research are briefly reviewed. In Session 3, three widely used measures of price discovery, the PT/GG, IS and MIS methods are discussed. In Session 4, we present and discuss our main empirical results. Finally, section 5 concludes the chapter.

3.2: Literature Review

Information-based microstructure models demonstrate that new information becomes impounded in prices as a result of trading by informed traders. If informed traders are more likely to choose one particular market to reveal their private information, prices on this market tend to lead prices on other markets.

3.2.1 Theories of Price Discovery

Tse et al. (1999) proposed three hypotheses to explain the preference of informed trading based on different market structures and security designs. They are the leverage hypothesis, the trading cost hypothesis, and the market-wide information hypothesis. Ma (2008) put forward another hypothesis called the loan rule hypothesis, and Fu (2010) introduced the institutional investor hypothesis. Corredor, Ferrer, and Santamaria (2015) further suggest the investor sentiment hypothesis to study the spot and futures markets.

Leverage hypothesis

The leverage hypothesis argues that high-leverage securities provide a better price discovery. Intuitively, with the same amount of capital available, high-leverage instruments provide a higher return on investment than low-leverage instruments. Traders with superior information would therefore prefer to trade high-leverage instruments, holding other factors constant. In this sense, CSI300 futures contracts should lead the underlying market as futures contracts require a small initial margin and offer the highest leverage. Thus, the spot market impounds information at a slower rate.

Trading cost hypothesis

The trading cost hypothesis predicts that the security incurring a lower trading cost would attract more informed trading. Trading costs include commissions and bid-ask spreads. Because profit is reduced by trading costs, informed traders have an incentive to trade their information in the market with the lowest trading cost. Establishing spot positions in the CSI300 index through program trading is very expensive because it requires as many as 300 separate stock trades, each subject to brokerage commissions and bid-ask spreads. On the other hand, index futures contracts are quoted in very narrow spreads because the information asymmetry for a composite security is low

Loan rule hypothesis

The loan rule specifies that a short sale of security on stock exchange can take place only when the investor have loaned enough security from brokers. The rule is imposed on the trading of individual securities in the CSI300 index. Although most major Chinese stockbrokers promise offer loan stock to their clients, the loan functions are always impossible, because their security pools are lack of stocks. Futures contract trades are not subject to the loan rule. Given the absence of Loan rule, futures prices should incorporate information more efficiently especially during the market downturn.

Market-wide information Hypothesis

The literature also suggests that a basket of securities may be created for the purpose of trading on a particular subset of information. Subrahmanyam (1991) demonstrates that index derivatives allow liquidity traders to trade more efficiently, which implies that bundling securities with similar reactions to certain kinds of information facilitates trading on that information, thus enhancing the price discovery process.

Accordingly, index derivatives should enhance the processing of market-wide information. The significance of price discovery role of an index instrument depends on whether the design of security allows traders to disseminate and act on market-wide information efficiently. The market-wide information hypothesis argues that futures should play a more significant role in price discovery process than the spot market.

Institutional investor hypothesis

Bohl and Salm (2011) argues that the institutional trading significant affect the dynamic of stock index markets. Institutional traders are large investors holding broad-based portfolios, and they usually have superior market-wide information. However, in China, many institutional traders (such as mutual funds and pension funds) are restricted by regulation from trading on CSI300 index futures market. This in turn may favor the price discovery contribution of the spot market.

Investor sentiment hypothesis

Corredor, Ferrer, and Santamaria (2015) extend the literature to study the relationship between investor sentiment and price dynamics in the spot and futures markets. They analyze spot and futures contracts of S&P 500, CAC 40, DAX 30, FTSE 100, IBEX 35, and Euro Stoxx 50. They show that the correlation between spot and futures prices decreases significantly during periods of high investor sentiment and volatility shocks tend to have less impact during these periods. Their results support behavioral finance theories, which predict that there may be an increase in noise trading during a high investor sentiment period, reducing the arbitrage activity from rational investors who attempt to limit their own risk exposure.

Table 3.1 Ranks of price discovery function of index markets

Hypothesis	Index Futures	Index
Leverage Hypothesis	1	2
Trading Cost Hypothesis	1	2
Loan Rule Hypothesis	1	2
Market-wide Information Hypothesis	1	2
Institutional Investor Hypothesis	2	1
Investor Sentiment Hypothesis	1	2

The ranks are based on the implications of 6 hypothesis regarding the influence of market structure and security design. The ranking scale ranges from 1 (better price discovery function) to 2 (worse price discovery function). The table above is modified by Tse et.al (1999)

Table 3.1 ranks the price discovery function for the index and index futures markets according to the implications of the six hypotheses. The index market suffers from disadvantages in most cases and may not be likely to be the dominant market for price discovery. On the other extreme, the index futures market enjoys the advantages of high leverage, low trading costs, absence of an uptick rule, and tradability as a market-wide portfolio. In the futures market, however, the trading restriction applied to large institutional traders tends to weaken its price discovery role. It should be noted that the various hypothesis are not mutually exclusive, and the price discovery role of a single market could be the result of the joint effect of several factors.

Early study like Wahab and Lashgari (1993) find that both S&P 500 and FTSE 100 spot and futures prices are cointegrated and move together in the long-run. This suggests that both spot and futures markets are important in terms of price discovery. In a more recent work, So and Tse (2004) analyze minute-by-minute data of the Hang Seng index, the Hang Seng index futures, and the Hang Seng ETF fund. They show that these markets have different degrees of information processing abilities, although they are governed by the same set of macroeconomic fundamentals. Their testing methods include the common factor model, Hasbrouck and Gonzalo and Granger common-factor models and the multivariate generalized autoregressive conditional heteroskedasticity (M-GARCH) model. Their results confirm the trading cost hypothesis which states that stock index futures prices reflect information more timely than the underlying stock market due to lower transaction costs. As such, a futures market has a more dominant role in price discovery than the spot market.

Bohl et al. (2011) extend the literature by examining whether the existence of large individual investors, who are presumably act as noise traders, in the futures market would reduce the “informational contribution” of futures trading in price discovery. They hypothesize that trading of unsophisticated individual investors may bring more noises and lower the price signal quality. Their sample covers the Polish

WIG20 index futures market that once dominated by individual investors. A change in mutual fund regulation in 2004 caused the share of individual investors to decline and the share of sophisticated institutional investors to rise. They find that during the period that the market was dominated by individual investors, the futures market played a limited role in the price discovery process. They conclude that more active trading from institutional investors has made the futures market to be more efficient and better reflect the relevant information.

3.2.2 Evidence on price discovery

If market participants can access and assimilate information at low cost, asset prices are expected to rapidly reflect this information. In an efficient market, information processing should be expeditious and the most information efficient market (asset) should lead the others. Hence, information transmission or price discovery is an indication of the relative market efficiencies of related assets.

In general, three major empirical approaches have been put forward in the literature to study the price discovery process of similar financial assets. The first approach focuses on the lead-lag relationship between the prices of national markets, or between different securities. The process in which the information gets reflected in the price becomes even more interesting if there are more than one market where the same security or very similar securities trade. For example, the same stock may be listed in multiple countries or in multiple markets in the same country. Harris, McInish, Shoesmith, and Wood (1995) investigated the transmission of price information about IBM in different stock exchanges. Eun and Shim (1989) studied the transmission of stock prices between different countries. In this case, one would be interested to know which market reflects the new information first. This gives rise to the concept of dominant and satellite markets (Garbade & Silber, 1983). In the case of multiple listing in multiple countries, one would like to know if the price discovery takes place in the domestic or foreign markets. Stoll and Whaley (1990) and Chan (1992) examined information transmission between the stock index and index futures markets.

The second approach involves examination of the role of volatility in the price discovery process. Volatility spillovers are important in the study of information transmission because volatility is also another measure of information flow. Two seminal papers (French & Roll, 1986; Ross, 1989) show that variance is an important source of information. French and Roll (1986) found that asset prices are much more volatile during exchange trading hours than at other times and that this divergence is caused by differences in the flow of information. Ross (1989) proved that asset price volatility is related to the rate of information flow in competitive asset markets. Previous studies on volatility spillovers in different national stock markets include Hamao, Masulis, and Ng (1990), Susmel and Engle (1994), Lin, Engle, and Ito (1994), Karolyi (1995), Koutmos and Booth (1995), and Booth, Chowdhury, Martikainen, and Tse (1997). The general conclusion is that volatility in one market will spill over to another market. Examining the volatility spillovers among similar assets, Chan, Chan, and Karolyi (1991), Kawaller, Koch, and Koch (1990), and Koutmos and Tucker

(1996) considered information transmission between stock index and index futures markets. As with volatility spillovers among different national markets, empirical evidence indicates that the volatilities of similar assets tend to transmit to one another.

The third approach attracts even a great attention from academia in the study of how information is transmitted among different markets. Using the common factor (or implicit efficient price) among cointegrated prices, information sharing techniques, notably the Hasbrouck (1995) and the Gonzalo and Granger (1995) models, have been used to study the contribution of price discovery from closely related markets. Price discovery measures are defined based on a framework where the prices in different markets are non-stationary (unit-root) processes with the number of cointegrating vectors equal to the number of markets minus one. One of these measures is based on the permanent–transitory decomposition proposed by Gonzalo and Granger (1995) (PT/GG) where the permanent component, for identification, is assumed to be a linear function of the original series. As the permanent component is considered to reflect the efficient price driving the prices in all markets, this method, referred to as PT/GG method, uses the normalized linear coefficients as the measures of price discovery (Booth, So, & Tse, 1999; Booth, Lin, Martikainen, & Tse, 2002; Harris, McInish, & Wood, 2002). This method has some desirable properties. First, PT/GG method permits the hypothesis testing of a market’s contribution to price discovery. Second, it provides a unique price discovery measure. However, as the linear coefficient vector can be shown to be orthogonal to the error correction coefficient matrix, one of the limitations of this method is the fact that it ignores the innovation variances.

Hasbrouck (1995) suggested another measure of price discovery commonly known as information share (IS). This is one of the most commonly used methods. One of the attractive features of this method has to do with the fact that it incorporates both the system dynamics as well as the innovation variances. A study by Chu, Hsieh, and Tse (1999) investigated price discovery among the Standard and Poor 500's (S&P 500) index, S&P 500 futures, and the S&P 500 Depository Receipt markets. They found that the futures market is the dominant source of information, followed by the Depository Receipt markets, with the spot market contributing least. Hasbrouck (2003) found that for the S&P 500 and Nasdaq-100 indexes, most of the price discovery occurs in the small-denomination futures contracts (E-mini). These examinations of information sharing are important as they deepen our understanding of the reactions of different assets to the same set of macroeconomic information.

The Hasbrouck's (1995) measure, commonly known as Hasbrouck information share (IS), has received the most attention and has been applied in many empirical studies. In essence, the information share is the fraction of the variance of the random walk component of the market efficient price that can be attributed to a particular market, trading venue, or a dealer. Generally, time variation in Hasbrouck-type information shares could come from either of its two components: time variation in model parameters and time variation in residuals variances (market volatility). In their study on whether thinly traded futures markets fulfill their price discovery function, Adämmer, Bohl, and Gross (2016) control for time variation in the parameters by applying the Kalman filter. Observing that important public news and market responses mostly happen in a matter of seconds or minutes and market volatility show significant intraday time variation, Ozturk et al. (2017) argue that current information share methodologies which typically consider daily share of information are not able to answer questions about variation in price discovery over different parts of the day.

For the CSI300 index futures market, researchers have focused on the relationship between the CSI300 index futures simulation and the CSI300 index. For example, Yan et al. (2009) used the daily data to study the CSI300 index from October 30, 2006 to March 20, 2009, using a vector error correction model, a common factor model, and a two-variable EGARCH model with error correction. They found that the spot market plays a leading role in price discovery. Xing (2010) studied the linkage effect between CSI300 index simulation futures and CSI300 index, and found that the introduction of stock index futures had little effect on the volatility of the spot market, but increased the asymmetric effect of the spot market. Hua and Liu (2010) used 1-minute level data of CSI300 index futures and CSI300 index from April 16, 2010 to June 11, 2010. They found both cointegration relationship and the bi-directional relationship in CSI300 index and index futures markets, while the impact of CSI300 index futures is even greater. The CSI300 index futures market is 7 minutes ahead of the spot market, while the CSI300 index is only 2 minutes ahead of index futures. This indicates that the price discovery ability of the stock index futures is stronger, and the CSI300 index futures market has a dominant status and is a main driving force in price discovery process.

In summary, the empirical evidence reviewed above suggests that carefully modeling time variation in market information shares can provide a richer understanding of price discovery process and market dynamics. For example, Chen, Chung, and Lien (2016) derive daily information share based upon high-frequency data and connect it to daily market information. Herein, different daily information shares arise from varying daily distributions. Frijns et al. (2015) divide the total sample period into subsample periods based upon distinct market statistics and use daily data to compute subsample information shares. The differences between the information shares across different subsample periods illustrate the inconsistency. Existing studies on price discovery often implicitly assumes that relative contributions of different markets or trading venues to the efficient price innovations to be constant over the sample period. As Ozturk et al. (2017) point out, this may not always hold true in empirical data with large samples due to changes in the characteristics of underlying exchanges and securities—such as increases in trade volume and electronization of trading mechanisms. Therefore, over the past decade, there have been a growing interest in empirically examine the time variation in the shares of price discovery for individual markets.

Table 3.2 Reviews of some Relevant Studies on price discovery

Papers	Market	DATA	Testing Methods
Herbst (1987), Martens (1998), Chan (1991), Hasbrouck (2003)	S&P 500	Daily & intraday	GARCH models
Futures prices change significantly ahead of spot price changes. On the contrary, there is only weak evidence that index price changes precede futures price changes.			
Abhyankar (1995)	FTSE100, S&P 500	5-min	EGARCH models
FTSE100, S & P 500 index futures prices are both leading the spot prices			

Kim (1999)	NYSE, MMI, S&P 500	daily	VAR models
In the futures market, S&P500 leads, while the spot market is dominated by MMI index.			
Tse (1999)	DJIA, S&P500	daily	VECM
Futures market serves the dominant price discovery function. The leverage hypothesis and the uptick rule hypothesis explain its superior price discovery function.			
So and Tse (2004)	Heng Seng Index Futures	1-min	M-GARCH model
The futures market dominates the spot market in the price discovery process.			
Lihara (1996), Booth (1996), Covrig (2004),	Nikkei 225	Daily & intraday	Dynamics models
The futures return is up to 20 minutes ahead of the spot, and the spot return is only up to 5 minutes ahead of the futures return. The Nikkei 225 spot market information contribution ratio is 23%, the Osaka futures market is 44%, and the Singapore futures market 33%			
Ryoo & Smith (2004)	KOSPI 200	daily	M-GARCH model
The lead-lag relation is asymmetric with weaker evidence that the spot index leads futures and stronger evidence that the stock index futures market leads the spot market.			
Booth (1999), Gaul & Theissen (2008)	DAX	daily	Dynamics models
Spot and futures markets share the role of price discovery equally.			
Yan et al. (2009)	CSI300	Daily	VECM, EGRACH
The index market plays a leading role in price discovery, but there is no significant asymmetric two-way fluctuation spillover effect between the two markets.			
Xing (2010)	CSI300	Daily	TARCH model
The introduction of stock index futures has little effect on the volatility of the spot market, but increases the asymmetric effect of the spot market.			
Hua and Liu (2010)	CSI300	1-min	VEC model
Both cointegration relationship and the bi-directional price lead relationships in CSI300 index and index futures markets, while the impact of CSI300 index futures is even greater. CSI300 index futures market has a dominant status and is a mainly driving force in price discovery process.			

The list of literature focused on price discovery with papers, market, date and their corresponding empirical model.

The objective of this chapter is to extend our understanding of information processing by investigating how information is transmitted among the Chinese Stock Index markets. Intuitively, spot and futures markets having the same underlying asset are affected by the same information set. Hence, differences in their information transmission abilities reflect relative efficiencies in information processing. An examination of their information transmission processes will also enhance our understanding of the information processing abilities of different markets that are linked by the same set of economic fundamentals.

3.3: Methodology

Our first measure of price discovery, which would be referred to as PT/GG measure, is based on the permanent–transitory decomposition proposed by Gonzalo and Granger (1995). The second one is the IS measure proposed by Hasbrouck (1995). However, as the IS measure depends on the ordering of the series, different IS measures are obtained depending on the ordering of the series, which leads to the upper and lower bounds for the IS measure. And the third, MIS measured by Lien and Shrestha (2009), which modified and extended the IS measures of Hasbrouck (1995).

We will now present and discuss the basic framework on which both types of measure are based on. Let Y_t be an $n \times 1$ vector of unit-root series where it is assumed that there are $n-1$ cointegrating vectors. The system consists of a single common stochastic trend (Stock & Watson, 1988). The series have the following vector error-correction representation (Engle & Granger, 1987):

$$\Delta Y_t = \prod Y_{t-1} + \sum_{i=1}^{k} A_i \Delta Y_{t-i} + \varepsilon_t, \Pi = \alpha\beta^T \qquad (3.1)$$

where α and β are $n \times (n-1)$ matrices of rank $(n-1)$. The columns of β consist of the $(n-1)$ cointegrating vectors and each column of α consists of adjustment coefficients. The matrix Π is decomposed in such a way that $\beta^T Y_t$ consists of $(n-1)$ vectors of stationary series. The covariance matrix of the error term is given by $\mathrm{E}[\varepsilon_t \varepsilon_t^T] = \Omega$.

Following Stock and Watson (1988), Equation (3.1) can be transformed into the following vector moving average (VMA) representation (Hasbrouck, 1995):

$$\Delta Y_t = \Psi(L)\varepsilon_t \qquad (3.2)$$

Or, alternatively,

$$Y_t = Y_0 + \Psi(1) \sum_{i=1}^{t} \varepsilon_i + \Psi(L)\varepsilon_t \qquad (3.3)$$

As the series are cointegrated, the Engle–Granger representation theorem (Engle & Granger, 1987) implies the following (De Jong, 2002; Lehmann, 2002):

$$\beta^T \Psi(1) = 0 \quad and \quad \Psi(1)\, \alpha = 0 \qquad (3.4)$$

Therefore, Equation (3.3) can be written as (see De Jong, 2002, Equation (3.4))

$$Y_t = Y_0 + \beta_\perp \alpha_\perp^T \sum_{i=1}^{t} \varepsilon_i + \Psi(L)\varepsilon_t \qquad (3.5)$$

where $\alpha_\perp$ and $\beta_\perp$ are orthogonal vectors to α and β, respectively. Note that $\alpha_\perp^T \sum_{i=1}^{t} \varepsilon_i$ represents the common stochastic trend component, which follows a random walk process. Also note that $\Psi(1)\varepsilon_t$, which represents the long-run impact of innovations on prices, would be the main focus of the empirical analysis.

3.3.1 Permanent–Temporary Gonzalo–Granger Measure (PT/GG)

Gonzalo and Granger (1995) suggested a way of decomposing the vector of non-stationary series Y_t into permanent (common factor) component f_t (which is non-stationary or I(1) series) and transitory (stationary) component $\widetilde{Y}_t$. The identification of these components is achieved by assuming the following:

The permanent component is a linear function of the original series and the transitory component does not Granger cause the permanent component in the long run.

Under these identification conditions, the series Y_t can be written as follows:

$$Y_t = Af_t + \widetilde{Y}_t \qquad (3.6)$$

This method of decomposing the original series into permanent and transitory components will henceforth be referred to as PT/GG method. The permanent component f_t (under linearity condition) can be written as

$$f_t = \theta^T Y_t \qquad (3.7)$$

where θ is the $(\mathrm{n} \times 1)$ permanent component coefficient vector. The dimension of the permanent component (i.e., the number of permanent components) is equal to the number of common stochastic trends in the system, which, in this case, is equal to one. Therefore, in the case under consideration, f_t is a one-dimensional series obtained by taking the linear combination of the existing series as given by Equation (3.7).

The argument for using PT/GG method is based on the consideration that the permanent component represents the fundamental or efficient price. As each of the original non-stationary series potentially contributes to the permanent component (Equation (3.7)), one can use θ_i (the ith component of the coefficient vector θ) to measure the contribution of market i to the price discovery process. This is the approach taken by Booth et al. (1999, 2002) and Harris et al. (2002). For example, if $\theta_1 = 0$, this implies that the first market has no contribution to the price discovery. Similarly, if $\theta_2 = 0$, then the second market has no contribution to the price discovery. Specifically, Harris et al. (2002) suggested the use of the elements of θ as measures of price discovery after the normalization so that the sum of the elements is equal to 1.

Gonzalo and Granger (1995) have shown that $\theta = \alpha_{\perp}$, where $\alpha_{\perp}$ is a column vector orthogonal to the adjustment coefficient matrix a (Equation (3.1)); $\alpha_{\perp}^{T}\alpha = 0$. Therefore, the permanent component f_t can be written as follows:

$$f_t = \alpha_{\perp}^{T} Y_t \qquad (3.8)$$

In order to see the relationship between this representation and Stock–Watson common stochastic trend representation, Equation (3.5) can be substituted into Equation (3.8) to get the following (see De Jong, 2002):

$$f_t = \alpha_{\perp}^{T} Y_t = \alpha_{\perp}^{T} Y_0 + \alpha_{\perp}^{T} \beta_{\perp} \alpha_{\perp}^{T} \sum_{i=1}^{t} \varepsilon_i + \alpha_{\perp}^{T} \Psi(L) \varepsilon_t \qquad (3.9)$$

Or, alternatively,

$$f_t = \alpha_{\perp}^{T} Y_t = \alpha_{\perp}^{T} Y_0 + \delta \alpha_{\perp}^{T} \sum_{i=1}^{t} \varepsilon_i + \alpha_{\perp}^{T} \Psi(L) \varepsilon_t \qquad (3.10)$$

where δ is given by $\delta = \alpha_{\perp}^{T} \beta_{\perp}$. Therefore, it is clear that Gonzalo–Granger permanent component (or common factor) consists of the Stock–Watson common stochastic trend plus a stationary series. Therefore, Gonzalo–Granger permanent component is a non-stationary ($\mathrm{I}(1)$) process, but not necessarily a pure martingale or a pure random walk process (Hasbrouck, 2002).

3.3.2 Hasbrouck IS Measure

As mentioned earlier, in the situation under consideration, there are $(\mathrm{n}-1)$cointegrating vectors and this implies that the impact matrix $\Psi(1)$ has rank 1. Furthermore, in the case considered by Hasbrouck (1995), the rows of $\Psi(1)$ are identical. Let $\psi = (\psi_1, \psi_2, \dots, \psi_n)$represent the identical row of $\Psi(1)$. Note that $\psi\varepsilon_t$ constitutes the long-run impact of innovations on each of the prices. For the case where the covariance matrix Ω is diagonal (i.e., the innovations are independent), Hasbrouck (1995) defines the IS of market j as follows:

$$S_j = \frac{\psi_j^2 \Omega_{jj}}{\psi \Omega \psi^T} \qquad (3.11)$$

where ψ_j is the jth element of ψ. The IS measure when the covariance matrix is not diagonal is given by (Hasbrouck, 1995)

$$S_j = \frac{\left([\psi \mathrm{F}]_j\right)^2}{\psi \Omega \psi^T} \qquad (3.12)$$

where F is the Cholesky factorization of Ω and $[\psi \mathrm{F}]_j$ represents the jth element of the row vector ψF. As the Cholesky factorization depends on ordering, the IS computed using Equation (3.12) will depend on the particular ordering. By considering all possible orderings, one can compute the upper and lower bounds on IS (see Hasbrouck, 1995 for the detailed derivations).

3.3.3 Modified Information Share (MIS) Measure

In this section we will briefly discuss the way in which the IS bounds can be eliminated. One shall look at the Hasbrouck IS measure with independent innovations from a different perspective. Note that in this case of independent innovations, $\Omega = \mathrm{diag}(\Omega_{11}, \Omega_{22}, \ldots, \Omega_{nn})$. Consider the following factor structure:

$$\varepsilon_t = \hat{F} z_t, E[z_t] = 0, E[z_t z_t^T] = I \qquad (3.13)$$

where $\hat{F}$ ($\mathrm{n} \times \mathrm{n}$ matrix) is chosen such that $\Omega = \hat{F}\hat{F}^T$, i.e. $\hat{F} = \mathrm{diag}(\sqrt{\Omega_{11}}, \sqrt{\Omega_{22}}, \ldots, \sqrt{\Omega_{nn}})$. Then, the variance of $\psi \varepsilon_t$, is given by

$$\psi \Omega \psi^T = E[\psi \varepsilon_t \varepsilon_t^T \psi^T] = E\left[\psi \hat{F} z_t z_t^T \hat{F}^T \psi^T\right] = \hat{\psi} \hat{\psi}^T = \textstyle\sum_{i=1}^n \hat{\psi}_i^2 \qquad (3.14)$$

where $\hat{\psi} = \psi\hat{F} = (\hat{\psi}_1, \hat{\psi}_2, \ldots, \hat{\psi}_n)$. Equation (14) shows a way of decomposing the variance $\psi\Omega\psi^T$ into separable additive parts. Then, the IS of market j can be defined as

$$S_j = \frac{\hat{\psi}_j^2}{\sum_{i=1}^{n} \hat{\psi}_i^2} = \frac{\hat{\psi}_j^2}{\hat{\psi}\Omega\hat{\psi}^T} \qquad (3.15)$$

The IS measure for market j given by Equation (3.15) is the same as the one given by Equation (3.11) where it has been assumed that the innovations are independent.

However, for a more general case where the innovations are not independent (i.e., the matrix Ω is not diagonal), the factor structure that satisfies the condition given by Equation (3.13) is not unique. Hasbrouck (1995) chooses F to be the Cholesky factorization of Ω. Unfortunately, this leads to the IS that would depend on the ordering of the series. It would be more logical to choose the factor structure that leads to IS being independent of ordering. This is what we propose in the chapter. Next, the new factor structure would be discussed.

Here, the use of the factorization matrix that is based on the correlation matrix is suggested. Specifically, let Φ represent the innovation correlation matrix. Let Λ represent the diagonal matrix with diagonal elements being the eigenvalues of the correlation matrix Φ, where the corresponding eigenvectors are given by the columns of matrix G. Finally, let V be a diagonal matrix containing the innovation standard deviations on the diagonal;$\mathrm{V} = \mathrm{diag}(\sqrt{\Omega_{11}}, \sqrt{\Omega_{22}}, \ldots, \sqrt{\Omega_{nn}})$. Then, the following transformed innovation z_t^* can be shown to have zero mean and identity matrix as the covariance matrix; i.e., $E[z_t^*] = 0$ and $E[z_t^*(z_t^*)^T] = I$. Then, one has the following factor structure for innovations:

$$\varepsilon_t = F^* z_t^* \tag{3.16}$$

where $F^* = \left[G\Lambda^{-1/2}G^T\mathrm{V}^{-1}\right]^{-1}$. Note that $\Omega = F^*(F^*)^T$. Under this factor structure, the MIS is given by

$$S_j^* = \frac{\psi_j^{*2}}{\sum_{i=1}^{n}\psi_i^{*2}} = \frac{\psi_j^{*2}}{\psi\Omega\psi^T} \tag{3.17}$$

where $\psi^* = \psi F^*$. It is important to note that under this new factor structure, the resulting ISs are independent of ordering. Therefore, this leads to a measure of price discovery that is order invariant but not unique. Due to the use of square-root matrix, one ends up with lack of uniqueness problem. The new measure is referred to as MIS. Note that when the innovations are not independent, it is necessary to choose a factor structure. As there are many possible factor structures one can choose from, the obvious question is which factor structure should be adopted. It is felt that one should adopt the factor structure that has some desirable properties such as uniqueness. Other desirable properties could be related to the performance of various factor structures under Monte Carlo simulation. As MIS leads to a unique price discovery measure and, as it is shown later, it also performs well under Monte Carlo simulation, it is argued that MIS is a better measure in measuring the contribution of price discovery.

If the number of series considered is 2, one has the following:

$G = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$, $\Lambda = \begin{bmatrix} (1+\rho) & 0 \\ 0 & (1-\rho) \end{bmatrix}$ and

$$F^* = \begin{bmatrix} 0.5\left(\sqrt{1+\rho}+\sqrt{1-\rho}\right)\sigma_1 & 0.5\left(\sqrt{1+\rho}-\sqrt{1-\rho}\right)\sigma_1 \\ 0.5\left(\sqrt{1+\rho}+\sqrt{1-\rho}\right)\sigma_2 & 0.5\left(\sqrt{1+\rho}+\sqrt{1-\rho}\right)\sigma_2 \end{bmatrix}$$

Therefore, at least for the two-market case, MIS leads to some plausible conclusions. Firstly, the MIS of a market increases, ceteris paribus, with the increase in the corresponding element of ψ. This makes sense because the elements of the vector ψ represent the long-run impacts of one-unit innovation. Secondly, ceteris paribus, the MIS of a market would be higher for the market with a larger innovation variance. This also makes sense because the innovation variance is expected to represent the amount of information in the setup considered by Hasbrouck (1995). Thirdly, when the innovation correlation approaches zero, the MIS converges to the independent case given by Equation (3.11). Finally, when correlation approaches unity, the MIS would approach 50% for each market.

3.3.4 Comparison of PT/GG, IS, and MIS Measures

As both PT/GG method and IS-based methods are derived from the same framework (n non-stationary series with $(\mathrm{n}-1)$ cointegrating vectors), they are closely related. For example, the condition represented by Equation (3.4) (i.e., $\Psi(1)\,\alpha=0$) implies that the identical row of $\Psi(1)$ is orthogonal to the error-correction matrix; i.e., $\psi = \alpha_{\perp}$. As the coefficient vector θ, used by PT/GG, is also orthogonal to the error-correction vector, θ and ψ differ by a scalar multiple; i.e., $\theta = s\psi$, where s is a scalar. Therefore, it is clear that PT/GG method uses only information on ψ, whereas IS and MIS use information on both ψ and innovation covariance matrix Ω. This fact would help characterize the price discovery measures based on PT/GG method and IS method.

From the discussion presented thus far, one can summarize the characteristics of

PT/GG-based measure and the measure based on IS. PT/GG measure has some attractive features. First, PT/GG method leads to a unique measure of price discovery. Second, PT/GG method permits the hypothesis testing on the individual elements of θ. Therefore, a hypothesis test on a particular market's contribution to price discovery can be performed. IS-based method does not permit the hypothesis testing unless the innovations are independent. However, PT/GG method uses only the error-correction coefficients and completely ignores the innovation covariances. As to the IS-based method, the modification outlined in the study solves the uniqueness problem. Furthermore, IS and MIS methods incorporate both the error-correction coefficients as well as the innovation covariances. The IS-based methods also have possible theoretical appeal due to the fact that the underlying permanent component follows pure martingale process. However, it has one drawback in that it does not allow hypothesis testing. Therefore, both measures should be employed in the subsequent empirical analysis.

The simulation results from Lien (2009) indicate that MIS performs the best among the three price discovery measures considered where IS measure performs close to MIS. It is important to note that MIS clearly outperforms when both public and private information is present, a situation considered to be rather normal. Therefore, during normal period, when both public and private information is present or where neither market is the sole source of price discovery, it is believed that MIS would significantly improve the analysis by providing a unique and efficient measure of price discovery.

3.4: Data Descriptions and Empirical Results

3.4.1 Data Descriptions

Our sample covers about 60% of the market value of the Chinese stock market and is a fairly good representation of the overall market. In particular, this research analyses the intraday price at 5-minute, 60-minute level and daily closing prices of CSI300 index and CSI300 index futures from January 1, 2012 to December 31, 2018. As the trading of CSI300 index futures is from 9:15 to 15:15 and the trading hours of CSI300 index are from 9:30 to 15:00, only the data where the trading hours between the futures and spot markets overlap are used, that is, only CSI300 index futures data within 9:30 to 15:00 are retained. The data on CSI300 index and CSI300 futures are sourced from the China Financial Futures Exchange. Figure 3.1 displays the movement of both time series. It can be clearly seen that, during our sample period of 2012-2018, the movement of CSI 300 index futures market follows closely that of CSI 300 index market.

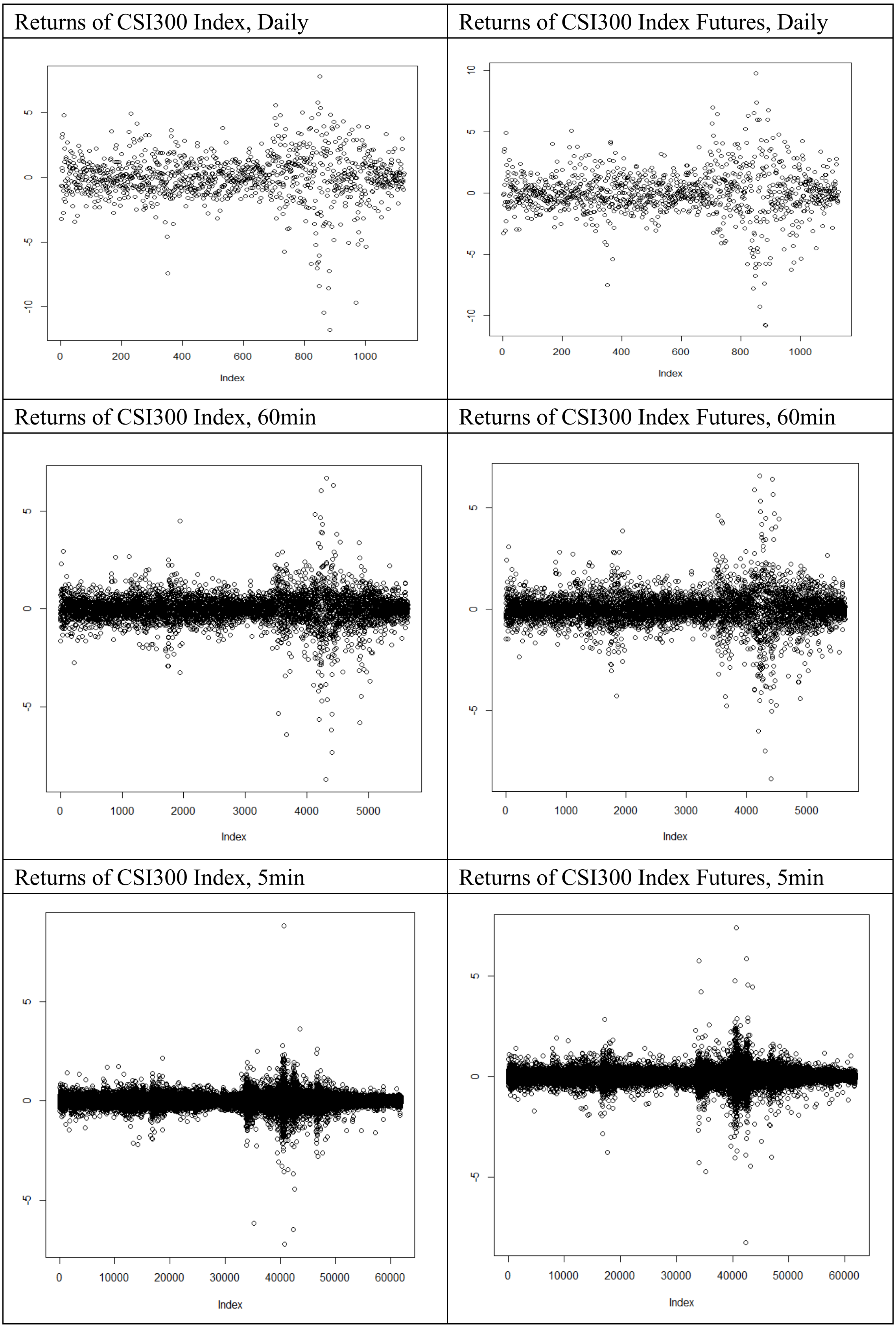
Both CSI300 index futures and underlying experienced negative returns. The variance of CSI300 index futures is larger than that of the underlying stock market. The CSI300 index futures and CSI300 index have a long right tail, and are right skewed. In addition, the LB (6) and LB (12) statistics are all statistically significant at the 1% level, indicating that the CSI300 index and its futures' returns have strong autocorrelation; In addition, the Augmented Dickey-Fuller (ADF) test results (with constant term and time trend term) confirm that CSI300 index and futures returns are both stationary. All the data in this chapter are collected from the dataset introduced in Chapter 1.4.1.

Figure 3.1 CSI300 Index and CSI300 Index Futures Prices

	
CSI300 Index daily close price	CSI300 Index Futures daily close price

The daily price of CSI300 index (left panel) and CSI 300 index futures (right panel) from 2012-2018. The closing price of the daily data is used. Source. The figure is taken from CFFEX http://www.cffex.com.cn/hs300/

Figure 3.2 CSI300 Index and Index Futures Returns



The scatter plots on the logarithm of spot and futures prices (i.e., the returns of spots and futures) with daily, 60 min and 5min sampling frequency for CSI300 Index (left panel) and CSI300 Index futures (right panel).

Table 3.3 Descriptive Statistics of CSI300 Index and Index Futures Returns

	$\Delta Spot$			$\Delta IF1$			$\Delta IF2$		
	5min	60min	Day	5min	60min	Day	5min	60min	Day
Mean	6.04 e-4	6.13 e-3	3.07 e-3	5.90 e-4	5.91 e-3	2.97 e-2	5.76 e-4	5.71 e-4	2.87 e-2
Std.Dev	0.22	0.73	1.77	0.25	0.79	1.87	0.25	0.82	2.00
Skewness	-0.87	-0.84	-0.90	-0.15	-0.24	-0.36	-0.19	-0.26	-0.14
Kurtosis	104.8	19.77	8.94	79.58	15.61	7.98	91.02	18.49	10.09
Jarque-Bera	2.68 e+7***	6.67 e+4***	1.81 e+3***	1.512 e+7***	3.74 e+4***	1.19 e+3***	2.00 e+7***	5.64 e+4***	2.36 e+3***
LB(6)	139.2***	35.36***	7.89	108.3***	32.97***	26.43***	99.61***	49.40***	31.63***
LB(12)	153.0***	56.65**	25.77**	142.8***	80.32***	54.95***	123.8***	104.9***	55.10***
$ARCH(6)$	951.5***	586.4***	272.4***	2365***	788.2***	466.3***	2043***	999.0***	623.3***
$ARCH(12)$	1348***	893.2***	411.6***	3552***	1419***	843***	2988***	1802***	1081***
ADF	-36.34 ***	-17.52 ***	-10.00 ***	-36.60 ***	-17.53 ***	-10.57 ***	-36.30 ***	-17.99 ***	-10.39 ***
PP	-61250 ***	-6143 ***	-1061 ***	-61500 ***	-6105 ***	-1089 ***	-62338 ***	-6112 ***	-1035 ***

The summary of statistics and unit-root tests results based on the logarithm of spot and futures prices. ΔSpot, ΔIF1, ΔIF2 list the first difference on the spot and futures prices with different time periods, IF1 is the contract that expires in the current month, and IF2 is the contract that expires in the next month. LB (6) and LB (12) are the logarithmic benefit Q statistic with lag periods of 6 and 12, respectively. The Q statistic is $Q = T(T+2)\sum_{j=1}^{k}\frac{\rho_j^2}{T-j}$, where ρ_j is the autocorrelation coefficient of j step of the lag, T is the number of sample, and k is the order of lag. ARCH (p) is a Lagrangian multiplier test used to detect residual autoregressive conditional heteroskedasticity, ARCH(6), ARCH(12) represents the LM test of the residual of the constant term at lags of 6 and 12. This is a test for the null hypothesis: the residual to the 6th order, the 12th order does not have the ARCH effect.
***, **, and * indicate the test statistic to be significant at 1, 5, and 10%, respectively.

The prices of index futures and spot are expressed as follows, where $C_{f,t}$and $C_{s,t}$are the closing prices of index futures spots of the day.

$$P_{f,t} = \ln(C_{f,t})$$

$$P_{s,t} = \ln(C_{s,t}) \qquad (3.18)$$

The returns of index futures and spots can be expressed as follows

$$R_{f,t} = P_{f,t} - P_{f,t-1}$$

$$R_{s,t} = P_{s,t} - P_{s,t-1} \qquad (3.19)$$

The vector error correction (VEC) representation with the t-distribution is:

$$R_{f,t} = \mu_f + \sum_{i=1}^{p} \alpha_{f,i} R_{f,t-i} + \sum_{j=1}^{q} \beta_{f,j} R_{s,t-j} + \gamma_f (P_{f,t-1} - P_{s,t-1}) + \varepsilon_{f,t}$$

(3.20)

$$R_{s,t} = \mu_s + \sum_{i=1}^{p} \alpha_{s,i} R_{s,t-i} + \sum_{j=1}^{q} \beta_{s,j} R_{f,t-j} + \gamma_s (P_{f,t-1} - P_{s,t-1}) + \varepsilon_{s,t}$$

(3.21)

where, $\varepsilon_t = (\varepsilon_{f,t}, \varepsilon_{s,t})'$, $\varepsilon_t | \Omega_{t-1} \sim t(0, H_t, \gamma)$, $\varepsilon_{f,t}$ and $\varepsilon_{s,t}$ are the residual terms for equations (3.20) and (3.21) above, $\Omega_{t-1}$is t-1 is the information set at time t-1, H_t is a time-varying condition covariance matrix of 2*2 order, and based on BIC, we choose the model dimension as: p = 2, q = 1.

Since stock index futures and stock index ($P_{f,t}$ and $P_{s,t}$) obey the first-order stationary process, $P_{f,t}$ and $P_{s,t}$ are selected for cointegration test and Granger causality test. The result of cointegration test with error terms and no trend (Johansen, 1991) and Granger causality test, are provided in Table 3.4 and Table 3.5, respectively.

Table 3.4 Johansen's cointegration Test between spot and futures price (contracts with 1 or 2-month maturity)

		Trace statistic	critical value		Trace statistic	critical value	
		Rank=0	5%	1%	Rank<=1	5%	1%
IF1	5min	242.46***	15.67	20.20	2.06	9.24	12.97
	60min	105.73***	15.67	20.20	1.85	9.24	12.97

	daily	75.04***	15.67	20.20	2.22	9.24	12.97
IF2	5min	82.89***	15.67	20.20	2.13	9.24	12.97
	60min	43.54***	15.67	20.20	1.91	9.24	12.97
	daily	41.04***	15.67	20.20	2.16	9.24	12.97

The list of Johansen's cointegration test between spot and future price for both IF1 and IF2. The trace test is used to test the null hypothesis that the number of cointegrating vectors is less than or equal to rank, where rank=0 (for no cointegration) or 1(for a single cointegrationg vector). *, **, and *** indicate 10%, 5%, 1% significance, respectively.

From comparing the statistic and critical value in the table 3.4, futures and spot data are rejected at the 1% confidence level, the null hypothesis Rank=0 is rejected, and the null hypothesis Rank=1 is accepted. This shows that there is only one feature vector, so there is a cointegration relationship between stock index futures and stock markets ($P_{f,t}$ and $P_{s,t}$). That is, in a short period of time, the futures and stock prices may deviate from equilibrium, but in the long run, they maintain an equilibrium relationship.

Table 3.5 Granger causality test between price of CSI300 index and index futures

	Null Hypothesis	F-Statistics	Probability Value
5min	$P_{s,t}$ is not the Granger reason for $P_{f,t}$	240.06	< 2.2e-16 ***
	$P_{f,t}$ is not the Granger reason for $P_{s,t}$	8.46	9.54e-13 ***
60min	$P_{s,t}$ is not the Granger reason for $P_{f,t}$	5.28	3.43e-07 ***
	$P_{f,t}$ is not the Granger reason for $P_{s,t}$	2.39	0.011 *
day	$P_{s,t}$ is not the Granger reason for $P_{f,t}$	2.87	0.0024 **
	$P_{f,t}$ is not the Granger reason for $P_{s,t}$	2.86	0.0024 **

The list of Granger causality test between CSI300 index and index futures with different sampling frequency (5min, 60min, daily).

The Granger causality test results reported in Table 3.5 suggest that neither futures nor spot ($P_{f,t}$ and $P_{s,t}$) are Granger's reasons for each other, indicating that there is not a mutual Granger causal relationship between CSI300 index futures and index market. At each independent time point, the prices of index futures and index are relatively independent and have no causal relationship with each other.

3.4.2 Price Discovery Analysis of CSI300 Markets

Price discovery, referred to the process by which new information is impounded into prices, is probably the most important function of financial markets. As it is often the case that there are more than one market or trading venue where the same security or very similar securities can trade, or when both a security and its derivatives are traded, one of the long-standing key issues is how to estimate the contribution of each market to the price discovery process. The empirical finance literature has proposed and used a variety of methods for estimating price discovery.

In this session, we use the three widely used methods outlined above to analyze the price discovery contribution of CSI300 index futures market (with different frequency of data and contract maturity). In addition, we analyze whether there is any difference in its price discovery capabilities before and after regulation reforms in 2015.

3.4.2.1 PT/GG Measure

Based on the Gonzalo and Granger (1995) model for the whole period and daily data, the common factor coefficients are 0.25 (index) and 0.75 (futures). These results show that the futures market is the main driving force in the price discovery process.

Table 3.6 Price discovery performance of CSI300 index futures (IF1) PT/GG

	Before		After		Whole	
	Index	Index Future	Index	Index Future	Index	Index Future
5min	0.46(0.11)	0.54(0.15)	0.39(0.11)	0.62(0.17)	0.42(0.14)	0.58(0.17)
60min	0.02(0.01)	0.98(0.01)	0.33(0.08)	0.67(0.21)	0.12(0.07)	0.88(0.05)
daily	0.37(0.13)	0.63(0.12)	0.30(0.07)	0.70(0.24)	0.25(0.11)	0.75(0.18)

The list of price discovery performance of IF1 denotes by PT/GG with different sampling frequency (5min, 60min and daily). The standard errors of parameters are given in the parentheses. The definition of before, after, whole is as same as Table 2.3.

According to Table 3.6, index futures are leading spot market in terms of price discovery at the daily level. However, at the 5-min level, the difference between futures (54%) and spot (46%) is not as obvious. This is because there are many individual retail investors in CSI300 index futures market (Xiong et al, 2010;Yang et al, 2016), and their transactions generate a lot of noise owing to their unpredictable behavior (Wei et al, 2015), which reduces the efficiency of stock index futures price discovery. This coincides with Institutional Investor Hypothesis.

After the regulation reforms, at the 60-min level, the largest leading percentage of index futures decreased significantly (from 98% to 67%). According to the market-wide information, price discovery role of an index instrument depends on whether the design of market allows traders to disseminate and act on market-wide information efficiently. It shows that the regulation reform interfered with the price discovery capability at the 60-min level mostly.

Table 3.7 Price discovery performance of CSI300 index futures (IF2) PT/GG

	Before		After		Whole	
	Index	Index Future	Index	Index Future	Index	Index Future
5min	0.20(0.13)	0.80(0.11)	0.40(0.18)	0.60(0.21)	0.27(0.06)	0.73(0.13)
60min	0.16(0.11)	0.84(0.11)	0.46(0.21)	0.54(0.25)	0.25(0.08)	0.84(0.11)
daily	0.09(0.07)	0.91(0.04)	0.10(0.03)	0.90(0.05)	0.08(0.03)	0.92(0.05)

The list of price discovery performance of IF2 denotes by PT/GG with different sampling frequency (5min, 60min and daily). The standard errors of parameters are given in the parentheses. The definition of before, after, whole is as same as Table 2.3.

Based on Table 3.7, IF2's price discovery performance is consistent. As the frequency of data increases, the leading position of futures is gradually decreasing (from 92% to 84% and 80%). After the regulatory reforms, the leading position of futures suddenly dropped significantly in intraday (from 84% to 54% in 60-min, and from 80% to 60% in 5-min), because the intraday transaction fees have been significantly increased by stricter trading restrictions. These results are in line with the trading cost hypothesis.

3.4.2.2 IS Measure

Our results of the average information shares: 5.47% (spot), 94.53% (futures), are similar to that of Hasbrouck's (1995). In addition to the daily level results at IF1, the average information sharing at the 60-min and 5-min level ranges from 75% to 95%. The results of IF2 are slightly weaker than IF1, but also in the range of 75% to 95%. These results indicate that CSI300 index futures dominate the price discovery process.

Results reported in Table 3.8 and 3.9 are also in line with the trading cost hypothesis, indicating that as the frequency of data increases, the leading position of futures reduces. However, after the regulations were tightened, the average information shares of IF2 increased to 86.26% (daily), 96.18% (60-min), and 97.9% (5-min) as shown in Table 3.9. Consistent with the market-wide information hypothesis, it means that the futures are still in a leading position. After the trading in current month's contract is restricted, the investors appear to choose trader in the next month's contract and thus making it an important venue for price discovery.

Table 3.8 Price discovery performance of CSI300 index futures (IF1) IS

	Before				After				Whole			
	Index		Index Future		Index		Index Future		Index		Index Future	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
5min	0.06	0.44	0.56	0.94	0.11	0.21	0.79	0.89	0.06	0.44	0.56	0.94
60min	0.03	0.06	0.94	0.97	0.08	0.96	0.04	0.92	0.03	0.06	0.94	0.97
daily	0.01	0.02	0.98	0.99	0.03	0.11	0.89	0.97	0.01	0.10	0.90	0.99

The list of price discovery performance of IF1 denoted by IS with different sampling frequency (5min, 60min and daily). The definition of before, after, whole is as same as Table 2.3.

Table 3.9 Price discovery performance of CSI300 index futures (IF2) IS

	Before				After				Whole			
	Index		Index Future		Index		Index Future		Index		Index Future	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
5min	0.08	0.55	0.45	0.92	0.02	0.02	0.98	0.98	0.08	0.55	0.45	0.92
60min	0.03	0.24	0.76	0.97	0.03	0.04	0.96	0.96	0.03	0.24	0.76	0.97
daily	0.09	0.18	0.82	0.91	0.09	0.18	0.82	0.91	0.01	0.09	0.91	0.99

The list of price discovery performance of IF2 denoted by IS with different sampling frequency (5min, 60min and daily). The definition of before, after, whole is as same as Table 2.3.

3.4.2.3 MIS Measure

The results of MIS measure reported in Table 3.10 and Table 3.11 are slightly different from that of PT/GG. At the daily level, IF1 was only 64.22% ahead for the whole period, and IF2 was only 61.11%. At the intraday level, the price discovery contribution of index future is almost equal to that of spot market.

Table 3.10 Price discovery performance of CSI300 index futures (IF1) MIS

	Before		After		Whole	
	Index	Index Future	Index	Index Future	Index	Index Future
5min	0.48	0.52	0.50	0.50	0.48	0.52
60min	0.50	0.50	0.52	0.48	0.50	0.50
daily	0.48	0.52	0.46	0.54	0.36	0.64

The list of price discovery performance of IF1 denoted by MIS with different sampling frequency (5min, 60min and daily). The definition of before, after, whole is as same as Table 2.3.

Therefore, based on the MIS measure, neither the CSI300 futures nor the spot has a significantly lead to another in terms of price discovery. Simulations considered by Hasbrouck (2002) indicate that MIS performs better than the IS measure. The same simulations also indicate that MIS is better compared to the PT/GG method. It shows that the price discovery ability of CSI300 index futures is more questionable under the better methods, like MIS measure. Possible reasons is that the 2015 policy regulations which leads to the decline of innovation variance.

Table 3.11 Price discovery performance of CSI300 index futures (IF2) MIS

	Before		After		Whole	
	Index	Index Future	Index	Index Future	Index	Index Future
5min	0.52	0.48	0.29	0.71	0.48	0.52
60min	0.51	0.49	0.43	0.57	0.51	0.49
daily	0.43	0.57	0.43	0.57	0.39	0.61

The list of price discovery performance of IF2 denoted by MIS with different sampling frequency. The definition of before, after, whole is as same as Table 2.3

As shown in Table 3.11 the information share of IF2 is similarly to that of IF1. Surprisingly, when the regulations were tightened in 2015, at the 5-min level, the information share of futures contract IF2 reaches 70.8%. According to Institutional Investor Hypothesis, due to tighten of regulations, more institutional investors chose to trade in the next month contract. This finding has an important implication for investors. When investors face a sudden increase in the trading cost, they can move to trade with a far month futures contract. In particular, as our results indicate, the next month contract may be more informationally efficient than the current-month contract.

3.4.2.4 Comparisons with other Futures Markets

In this chapter, we empirically estimated the price discovery contribution of the spot and futures markets using the MIS approach as outlined in the previous section. For comparison, we also reported the results obtained by the Gonzalo–Granger Permanent–Temporary Measure and Hasbrouck IS methods. Furthermore, we have also repeated our analysis using the daily spot and futures data on S&P 500, TOPIX, and FTSE 100 indices to comparatively assess the importance of CSI300 index futures in price discovery process. In each case, main futures contracts are used and the sample period remains the same period 2012-2018. All the relevant data are obtained from Reuters. Once again, only the data where the trading hours of the futures and spot markets overlap are included in this comparative analysis.

The estimation results based on PT/GG, IS, and MIS are summarized in Table 3.12. For all three international indices, the IS upper and lower bounds are far apart. Based on Modified IS results, it is clear that price discovery takes place mostly in the futures market rather than the spot market for all the markets, especially at the daily level.

Table 3.12 Price discovery contribution of the major stock index futures markets

	Spot Market				Futures Market			
	PT/GG	MIS	Lower Bound	Upper Bound	PT/GG	MIS	Lower Bound	Upper Bound
CSI300	0.25	0.36	0.0087	0.10	0.75	0.64	0.90	0.99
FTSE 100	0.16	0.23	0.0060	0.64	0.85	0.79	0.36	0.99
TOPIX	0.24	0.39	0.010	0.90	0.76	0.61	0.10	0.99
S&P 500	0.18	0.29	0.0021	0.78	0.82	0.71	0.22	1.00

The comparison of daily price discovery contribution for different index in spot and futures market with different denotation. The data of FTSE 100, TOPIX, S&P 500 are collected from Reuters.

Overall, basing on the results reported in Tables 3.6 to 3.12, the following observations can be drawn with regards to the price discovery role of CSI300 futures. First, index futures market is leading the price discovery process in the Chinese market. Based on the daily results, the price discovery contribution of CSI300 index futures are 75% (PT/GG), 95% (IS), and 64% (MIS). Although the results of MIS is slightly weaker, these all indicate that CSI300 futures lead the spot significantly in terms of information share. Similar to Lien (2009), and consistent with the transaction cost hypothesis, it is found that price discovery takes place mostly in the futures market. This finding is also consistent with that of Garbade and Silber (1983), Oellermann, Brorsen, and Farris (1989), Schroeder and Goodwin (1991), Yang, Bessler, and Leatham (2001), and So and Tse (2004). It is also important to point out that the finding that futures dominate price discovery is also in line with the argument put forward by Garbade and Silver (1983) which suggests that price discovery is determined by the relative number of participants in each market (i.e., trading volume or liquidity).

Second, although regulatory reforms reduce the information share of index futures, CSI300 futures market is still the dominant market. As discussed before, the Chinese regulatory authorities issued additional restrictions on trading of stock index futures in September 2, 2015. This chapter is the first empirical study of the impact of these regulation reforms on the price discovery function of CSI300 index futures market. Our results show that the information share of CSI300 index futures drop significantly after 2015. This could be due to the fact that, when stricter regulation is introduced, the intraday transaction fees would significantly increase. This sudden increase in the cost of intraday trading reduced the price discovery capability of CSI300 index futures market and reduced its information efficiency. Nevertheless, the transaction cost of futures is still relatively lower than that of stock market, CSI300 futures market remains an important venue in which price discovery takes place.

Third, with regards to the maturity of futures contracts, our results indicate the most current month contract of CSI300 futures (IF1) lead the next-month contracts (IF2) in information shares. In particular, using IS and MIS measures and at the 5-min level, we find that the price discovery contribution of IF2 reached to 98% (IS) and 71% (MIS) after regulation reforms. According to Institutional Investor Hypothesis, due to tighten of regulations, more institutional investors chose to trade in the next month contract. Switching between the current month and next month contracts can provide an important reference and indication for investor trading behavior.

Fourth, there appear to be different results from the PT/GG, IS and MIS methods. CSI300 futures market leading significantly in both PT/GG (75%) and IS (95%) methods. However, the MIS measure shows that the information share of spot and futures are very close, especially at the intraday level. Simulations considered by Hasbrouck (2002) indicate that MIS performs better than IS method. The same simulations also indicate that MIS is better compared to the PT/GG method. Since the CSI300 index futures market has just been launched less than 10 years in 2010, the information shares of CSI300 stock index futures could no doubt be further enhanced.

Finally, compared with other more developed stock index futures markets on TOPIX FTSE and S&P500 indices, the difference of CSI300 market is not that large. The price discovery performance of CSI300 index futures (75%) is close to that of TOPIX (76%), but slightly worse than FTSE (89%) and S&P500 (82%) according to the PT/GG method. Using the same time interval (2012-2018), the relatively new Chinese stock index futures market is comparable to that of other mature futures markets in terms of price discovery, indicating that in Chinese futures markets information relating to the fundamental value is reflected in the price rather rapidly.

3.5: Conclusions

3.5.1 Summary of Findings

This chapter use the three widely used methods, which are PT/GG, IS, and MIS, to analyze the price discovery contribution of CSI300 index futures market (with different frequency of data and contract maturity). In addition, we analyze whether there is any difference in its price discovery capabilities before and after regulation reforms in 2015. Then, we compare the price discovery contribution of CSI300 futures with that of FTSE100, TOPIX and S&P500 futures markets. The results suggest that the price discovery capability of CSI300 market is similar to that of mature markets. There is no significant difference in the information share of the Chinese futures markets and other markets (based on MIS measure). It can be arguing that after only 10 years CSI300 futures contract has become an important tool for both domestic and foreign investors to discover the information relating to the underlying asset. For the results of CSI300 index futures and the spot market, CSI300 index futures play a dominant role in the price discovery process, at the daily level. However, with intraday data, regardless of the current or the next month's futures contract, its price discovery ability does not significantly exceed that of index market.

Overall, this chapter make the following contributions to the extant literature. Firstly, this chapter is the first study to analyze the price discovery of CSI300 index futures before and after regulators reforms, using different measurement methods, various frequency of data, and two futures contracts with different maturity.

Secondly, the performance of the CSI300 futures market and other mature futures market is compared using different price discovery measures and we find that the performance of Chinese futures market is not significantly different to other mature markets in terms of price discovery capability. Finally, it is also found that the futures market dominates price discovery only at the daily level, but in the intraday, the price discovery ability of futures and spot are rather similar.

There are two possible reasons of why the price discovery ability of futures market is not significant at the intraday level: One, Chinese futures market is still immature, there are much more retail speculators than mature markets, and the intensity of institutional investor trading is still gradually increasing. In a short period of time, arbitrage trading cannot be carried out quickly which in turn affects the speed at which index futures prices return to their fundamental value, so that in a short period of time, futures market do not play a leading role in the price discovery process. The other reason, according to traditional theory, is that information transfer occurs in the markets which have lower costs, higher leverage, and fewer regulatory restrictions. Since 2015, due to regulation reforms, the intraday transaction in CSI300 futures market has to face an increase in trading fees and margins, resulting in higher costs than spot trading. Therefore, the CSI300 futures market is not significantly leading the spot market at the intraday level (as indicated by our results at 5min and 60min level) supporting the trading cost hypothesis.

3.5.2 Further Research Agenda

Previous literature has extensively analyzed price discovery and lead–lag relationships between stock index futures and spot markets (for example, Booth et al., 1999; Chou & Chung, 2006; Covrig et al., 2004; Gaul & Theissen, 2008; Stoll & Whaley, 1990; Wahab & Lashgari, 1993). There is a widespread evidence that futures trading contributes to price discovery and thus to the efficiency of financial markets. It is important to notice that most of the markets under investigation in existing studies are similar in terms of investor structure and market characteristics. In the majority of cases, futures markets are characterized by a high share of institutional trading. Indeed, previous literature fails to consider the potential effect of the investor structure, especially the role of dominant individual investors, on the relative price discovery contributions of stock index and futures markets. The change in investor structure has led to an increased information content of futures prices. As the number of institutional traders continues to grow in the Chinese stock index futures market, we expect the price discovery contribution of the CSI300 index futures market to improve further. This would be an interesting area for future research.

The results of this chapter also highlight an important link between the role of derivatives markets in the price formation process and the investor structure. In line with previous literature, we find evidence that the Chinese futures market performs an important price discovery function and contributes to informational efficiency of the market. However, our findings also suggest that this price discovery role critically hinges on the participation of well-informed institutional investors. This has important implications for emerging market regulators who face decisions regarding the design of domestic futures markets. While restricting market participation of institutions like pension funds may be popular with the public, it may also compromise the efficiency of domestic derivatives markets. Therefore, to reap the fruits of index futures trading in terms of increased stock market efficiency, regulators should not prohibit but rather encourage institutional futures trading. By contrast, small retail investors, consisting mostly of individual traders, generally have limited capital and lack financial knowledge and technical skills. Large investors are more likely to be institutions with professional skills and experience, such as mutual funds. It is natural to assume that large investors play a dominant role in price discovery. However, there is a lack of empirical studies on the contribution from the smaller traders to price discovery, especially in futures markets. In future research, one could investigate the impact of changes in market participants on the relative contribution of stock and futures markets to the price discovery process.

Chapter 4 - Efficiency of CSI 300 Index Futures Market and the Impact of Regulatory Reforms

4.1: Introduction

4.1.1 Research Background

Fama (1970, 1991) contends that a financial market can be considered as efficient if prices fully and instantly reflect all available information. However, market efficiency is not testable, and it must be tested jointly with an asset pricing model. Kenourgios (2004) concluded that derivatives market efficiency requires that derivatives prices equal expected spot prices at the contract maturity plus or minus a risk premium, which can be either constant or time varying. In other words, futures prices should be the unbiased predictor of subsequent spot prices only if both market efficiency condition and no risk premium condition hold, i.e., a joint hypothesis (Kenourgios, 2005). Tharavanij (2017) extend the literature and argue that, even in the case that futures prices are biased, it is difficult to distinguish empirically whether the forecasting bias is due to the failure of the markets to incorporate all relevant information leading to market inefficiency, or the existence of a risk premium. Markets may even be efficient and futures prices are unbiased in the long run, but in the short run, there could be inefficiencies and pricing biases. In addition, a risk premium itself may be time varying (Antoniou and Holmes, 1996). Therefore, this chapter aims to empirically investigate both market efficiency hypothesis and unbiasedness hypothesis in the context of Chinese Securities Index 300 futures to determine whether CSI300 futures market is efficient and if significant pricing bias exists.

Roberts (1967) and Fama (1970) define market efficiency into three categories:

weak form efficiency, semi-strong form efficiency, and strong form efficiency. The weak form efficiency indicates that all the information in the past prices is reflected in today's prices. The semi-strong efficiency implies that all publicly available information is incorporated into current prices. The strong form efficiency requires that all information in a market, whether public or private, is accounted for in asset prices.

If the rationality and risk neutrality of market participants are assumed in addition to the efficient market hypothesis, future prices would be equivalent to the expected values of spot prices, as shown in the following equation:

$$F_t = \mathrm{E}[S_{t+1}|I_t] \quad (4.1)$$

F_t denotes the price at time t of a futures contract expiring in time (t +1); $S_{t+1}$the spot price at time (t +1); and I_t is all available price information at time t. In reality, however, market participants are not necessarily risk neutral and markets thus have a risk premium. Therefore, a risk premium term is added to Equation (4.1) as follows:

$$F_t = \mathrm{E}[S_{t+1}|I_t] + v_t \qquad (4.2)$$

v_t denotes the risk premium and is assumed to be stationary. The risk premium has the possibility of variations in time and an expected value other than zero. Thus, a majority of research to date has used Equation (4.3) to validate Equations (4.1) and (4.2).

$$S_{t+1} = \alpha + \delta F_t + u_{t+1} \quad (4.3)$$

If spot and futures prices are both nonstationary processes, and S_{t+1} and F_t have a cointegrating relation with a cointegrating vector of (1, -1), then Equation (4.2), which represents the efficient market hypothesis, is supported. If S_{t+1} and F_t do not have a cointegrating relation, the deviation from the equilibrium is not incorporated into the price information and will thus be magnified over time. This phenomenon is against the idea of market efficiency. However, if the liquidity of spot market is significantly different from that of futures markets, the magnitude of price adjustment may be different between these two markets. The cointegrating relation may not be supported under these circumstances even if the markets are efficient. Furthermore, if the futures price is the unbiased estimator of the spot price, as shown by Equation (4.1), the additional condition $\alpha = 0$ also needs to be satisfied.

The notion that the futures price is the best forecast of the spot price is an implication of the efficient market hypothesis. In an efficient market, new information is reflected instantly in asset prices. If this is true, then price patterns are random, and no trading system based on past market behavior can do other than simply break even. The link between efficiency and forecastability arises from realizing that the difference between the current futures price and the future spot price represents both the forecasting error and the opportunity gain or loss realized from taking certain positions. The requirement that the forecasting error is zero on average is consistent with both market efficiency (the absence of profitable arbitrage opportunities) and the unbiasedness property of the forecaster.

Antoniou and Holmes (1996) extend the unbiasedness hypothesis derived from the arbitrage theory and argue that, given conditions of rational expectations and risk neutrality, the price of derivatives is an unbiased predictor of the spot price, without a risk premium. According to the unbiasedness hypothesis, derivatives (futures/forward) contract prices must be unbiased estimators of spot prices of the underlying asset that will be realized at the expiration date of the contract (Kavussanos, 2004). Investigation of the unbiasedness hypothesis for the index future market is interesting. The price discovery function provides a strong and simple theory of the determination of spot prices that may prevail in the future. If index futures prices fulfil their price discovery role, they should provide accurate forecasts of the spot prices, and consequently provide new information in the market and in allocating economic resources (Stein, 1981). The existence of inefficiency of index futures prices can increase the cost of hedging, assuming that the market investors and agents are fully informed when index futures price are settled in contracts.

Previous studies on the unbiasedness hypothesis focus mostly in the mature stock markets and commodity futures. The CSI300 futures contract is an interesting case for further analysis as it has a lower liquidity and is more prone to manipulation from participants than other mature markets. The question is then whether in this context a futures price can still efficiently incorporate all information in predicting a subsequent spot price. We intend to address this important question in this third empirical chapter.

Chinese stock index futures market has been introduced for nearly 10 years up to now. While some studies have examined its market efficiency (Yang et al., 2012), the existing researches concentrate on using daily data to study efficiency of CSI300 stock index futures market (Kenourgios et al., 2008). In addition, the Chinese stock market has recently taken a rollercoaster ride, as discussed before. From the beginning of 2015 until mid-June, the CSI 300 Index, which represents the broad Chinese A-share market, rose from 3500 to a high of 5178. Then it collapsed, losing over 34% in 20 days, with 1000 points erased in one week alone. Due to the pressure from regulators and the public, the CFFEX announced on August 25 that starting August 26, three measures were adopted to curb speculative trading in the index futures market. First, the initial margin for non-hedging trades would be raised from 10% to 12%, 15% and to 20% over the following 3 days. Second, any single day's total opening position greater than 600 contracts would be considered abnormal trade and be subject to increased scrutiny. Third, the clearing fees for intraday trades were adjusted upward to 1.15 basis points.

With the crisis developing further and the effect of government bailout measures quickly diminishing, September 2 witnessed the CFFEX announce yet another round of measures to curb speculative trade in the futures market. First, starting September 7, any single day non-hedging trading of over 10 contracts would be considered abnormal. Second, the initial margins for all non-hedging trading would be raised from 30% to 40%, and the initial margins for hedging trades would be raised from 10% to 20%. Third, the clearing fees for intra-day trades would be adjusted from 1.15 to 23 basis points. With these additional restrictions, index futures trading in China nearly came to a complete stop, as shown in Table 1.3 of chapter 1. (Please refer to Table 1.3 for further details of these regulatory reforms.) This rare regulatory reform, which placed direct limits on the number of trades, provides a unique setting to examine the impact of index futures trading in an order-driven spot market.

In chapter 3, we have investigated the price discovery function of the CSI300 Index futures and spots markets. This chapter will examine the efficiency of CSI300 futures, as well as the potential impact of regulatory reforms in 2015 on market efficiency.

4.1.2 Research Aim and Objective

Market efficiency has long been the main interest of many academic researches. Chinese stock index futures launched over nine years ago and since then it has gone through a rapid development period and a stagnation period. There are also a limited number of studies examining the efficiency of futures contracts in emerging markets. This chapter will therefore use 5-minute, 60-minute and daily level data to investigate the efficiency of Chinese stock index futures market from a perspective of weak form efficient market. Moreover, this chapter will analyze the change in market efficiency before and after the policy reforms. In particular, we aim to address the following research questions:

- Whether the Chinese Securities index future (CSI300) is informationally efficient?
- Whether, and to what extent, efficiency of CSI300 index futures was impacted by the regulatory reforms in 2015?

We employ unit root test and cointegration test techniques to examine the validity of market efficiency hypothesis and unbiasedness of futures price hypothesis in the Chinese stock index futures market, and to compares the efficiency before and after regulatory reforms. Overall, the results of this chapter should carry significant implications to market regulators and participants in formulating effective strategies.

4.1.3 Research Significance

The Chinese stock index futures markets have grown rapidly in the past few years. Against this background, it is of great significance to use multi-frequency data to empirically investigate the efficiency of CSI300 index futures market. In terms of methodology, this chapter employs similar techniques, namely, the cointegration and the error correction model (ECM), with previous studies such as Wahab and Lashgari (1993), So and Tse (2004), and Bohl, Salm, and Schuppli (2011) in investigating relationships between spot prices and futures prices. However, many studies failed to fully account for the stationarity of the net cost of carry. Brenner and Kroner (1995) show that, if the net cost of carry has a unit root, spot and futures prices could not be cointegrated. In addition, Brenner and Kroner (1995) find that cointegration can only exist when futures prices being analyzed is with a fixed time to maturity. To address these shortcomings of previous studies, this chapter first explicitly check for a stationarity of the net cost of carry before testing for a cointegration between spot and futures prices (Brenner &Kroner, 1995).

While there are a few empirical investigations in the efficiency of Chinese stock index futures market, these studies are based mainly on daily price data and limited evidence on efficiency of futures market at intraday level (Liao and Chou, 2013). Thus, this chapter will employ both daily and intraday market data to study efficiency of Chinese stock index futures market.

Finally, as the only derivative instrument available to investors for hedging the fluctuation and risk in the Chinese stock market, our empirical results on the efficiency and unbiasedness of CSI300 index futures (with different maturities and for different routes) should provide some important implications for investment decision-making.

4.1.4 Roadmap

The rest of this chapter is organized as follows. Section 4.2 is literature review. The efficient market hypothesis and unbiasedness of futures price hypothesis are discussed. In this section, the empirical evidence on unbiasedness of various futures markets (such as the freight forward market, commodity futures market and stock index futures market) will be presented. Section 4.3 explains the main sources of our data and testing methods. Unit root test, cointegration test and the Johansen cointegration procedure as well as our data selection and processing methods are outlined in this section. Section 4.4 reports the empirical result for efficiency of CSI300 stock index futures market. For the unbiasedness hypothesis, we consider all three possible scenarios - zero risk premium, a constant risk premium, and a time-varying risk premium. Finally, section 4.5 summarizes and concludes.

4.2: Literature Review

It has long been a debate in the literature on the most appropriate methods in testing the unbiasedness of futures markets. Empirically, academic researchers usually estimate variant of the following equation to test whether futures prices are unbiased predictors of future spot prices:

$$S_{t+1} = \alpha + \delta F_t + u_{t+1} \quad (4.3)$$

where S_{t+1} is the spot price at maturity time, and F_t is the futures price. The empirical test of the unbiasedness hypothesis involves the joint null hypothesis: $\alpha = 0$ and $\delta = 1$. Overall, the evidence from previous studies suggest that $\alpha > 0$ and $\delta < 1$; i.e., the unbiasedness hypothesis is rejected in the futures markets (Hein 1990).

The unbiasedness of forward exchange rate market is investigated in Hakkio and Rush (1989), Barnhart and Szakmary (1991), Luintel and Paudyal (1998), Norrbin and Reffett (1996) and Barnhart, McNown, and Wallace (1999). They test the unbiasedness for the one-month forward exchange rates for the British pound, German mark, Swiss franc, Canadian dollar, French franc, US dollar and Japanese yen. The first three studies report evidence against unbiasedness while the last two find evidence in favor of the hypothesis. In addition, the unbiasedness of forward commodity prices in the London Metal Exchange (LME) are examined by studies such as Chowdhury (1991) and Moore and Cullen (1995) and for the Commodity Exchange (COMEX) by Krehbiel and Adkins (1993).

The existing literature examining the behavior of commodity futures markets is fairly extensive. Early work focused primarily on studying the efficiency of futures markets and yielded diverse conclusions. Many studies provided evidence for efficient markets but an equally large number of studies provided evidence that contradicts an efficient market (unbiased futures price prediction) interpretation. For energy markets, Serletis (1991) found that the crude petroleum futures markets are efficient. Bopp and Lady (1991), however, found that either the spot or the futures price can be the superior forecast depending on market conditions, and the information content of the two-price series is essentially the same. A related literature has focused on the long-run properties of the spot and futures prices, within the cointegration framework (Crowder & Hamed, 1993; Moosa & Al-Loughani, 1994; Herbert, 1993; Walls, 1995; Peroni and McNown 1998; Gulen 1998), again finding mixed results. Switzer and El-Khoury (2007) performed tests on futures and spot prices for WTI transactions between January 1986 and April 2005 and find that $(\alpha, \delta) = (0,1)$. Furthermore, Maslyuk and Smyth (2009) examined whether crude oil spot and futures prices are cointegrated, using a residual-based cointegration test that allows for one structural break in the cointegrating vector. They investigated the US WTI and the UK Brent for the period between January 1991 and November 2008 and found that crude oil spot and futures prices are cointegrated with one structural break in the cointegrating vector.

More recent work has focused on the ability of futures prices to predict subsequent price changes. For instance, Alquist and Kilian (2010) and Alquist, Kilian, and Vigfusson (2012) find little evidence that oil futures prices systematically outperform random walks but also document that alternative sources of oil forecasts (statistical models, surveys of professionals, and policy‐makers) do not perform better. Chernenko, Schwarz, and Wright (2004) compare the properties of oil and natural gas futures prices to that of exchange rate and interest rate futures. Other attempts in improving on the forecast performance of futures prices have considered adjusting for risk premia (Pagano & Pisani, 2009) or using information from exchange rates (Chen, Rogoff, & Rossi, 2009; Groen & Pesenti, 2010).

4.2.1 Theoretical Framework

Using the cost-of-carry model, Brenner and Kroner (1995) examine whether the existence of cointegration between spot and futures prices depends on the time-series properties of the net cost of carry, called henceforth the "basis." More specifically, if the basis is stationary, then spot and futures prices are tied together, and they would be cointegrated. On the contrary, if the basis is not stationary, then spot and futures prices will move apart, and they will not be cointegrated. In this case, spot price, futures price, and basis will form a three-variable cointegration with a cointegrating vector of (1, -1, 1).

Brenner and Kroner (1995) also pointed out that cointegration can only exist when studying time series of futures prices with fixed time to maturity. Therefore, any regression of spot and future prices on a fixed expiry date would have an error term that moves toward zero as futures contracts are about to expire. This means that the variance of this residual decreases through time, implying non-stationarity. As a result, cointegration cannot exist. Their results suggest that the appropriate cointegrating vector for stock index futures would involve stock index, futures prices, and the basis, which, in this case, are the basis between futures and underline assets. If futures price is non-stationary, then spot and futures prices will not be cointegrated as the basis is required in the cointegrating vector. They also prove that if the basis is non-stationary, then the unbiasedness hypothesis cannot hold. Intuitively, the gap between the spot and futures price contains the basis. If this basis is non-stationary (i.e., contains a unit root), then it must be strongly serially correlated. However, serial correlation in the forecast error violates the unbiasedness hypothesis.

To investigate the unbiasedness of futures prices ($\delta = 1$) or market efficiency ($\alpha = 0$, $\delta = 1$). The null of $\delta = 1$ is interesting as well, since in this case the basis has no predictive content for subsequent price changes. Hence, while we will focus in our empirical estimates primarily on the unbiasedness hypothesis, the additional questions of whether δ is different from zero as well as the market efficiency condition will also be of interest.

4.2.2 Empirical Evidence

There have been quite a few studies investigating the unbiasedness hypothesis between spot and futures prices in index futures market. A unique feature of this market is that the underlying asset is a stock market index, which cannot be stored.

The traditional theory on the relationship between spot and derivatives prices of continuously storable commodities are thought to be related through a “cost-of-carry” relationship (Working, 1970). The cost-of-carry formula determines the relationship between spot and derivatives prices and any deviations from this relationship will be restored in the market through riskless-arbitrage (Kolb, 2000). The relationship between spot and derivatives prices for non-storable commodities is examined in studies such as Brenner and Kroner (1995), Eydeland and Geman (1998), Geman and Vasicek (2001), and Bessembinder and Lemmon (2002) in the electricity derivatives markets. As mentioned above, the non-storable nature of the index market implies that spot and index futures prices may not be closely linked by a cost-of-carry (storage) relationship, as in agricultural derivatives markets. Overall, the existing empirical evidence, based on cointegration techniques, is mixed; it seems that the conclusion of unbiasedness depends on a number of factors such as the type of contract, the maturity of the contract, the market, and the time-period under investigation.

4.2.2.1 Unbiasedness Hypothesis in financial markets

Kleopatra et al. (2006) demonstrate why the forward rate forecast error, the basis, and the forward premium are serially correlated, and they develop econometric tests of the "unbiasedness hypothesis" (sometimes called the "simple efficiency hypothesis") in various financial markets. The unbiasedness hypothesis is so prevalent in the finance literature that many different types of tests have been developed. Much attention has been given to the possibility that two or more assets might share the same stochastic trend, i.e., that the assets might be cointegrated. For example, the following sets of financial time series (among many others) have been found to be cointegrated: sets of exchange rates (Baillie and Bollerslev, 1989); foreign currency spot and futures rates (Kroner and Sultan, 1993); interest rates of different maturities (Engle and Granger, 1987); interest rates in different countries (Akella and Patel , 1991); foreign currency spot and forward rates (Barnhart and Szakmary, 1991); dividends and prices (Campbell and Shiller , 1987); equity markets in different countries (Taylor and Tonks, 1989); stock prices within a given industry (Cerchi and Havenner, 1988); and size-ranked portfolios (Bossaerts , 1988).

4.2.2.2 Unbiasedness Hypothesis in Commodity futures

McKenzie and Holt (2002) investigate four agricultural commodity futures contracts by applying cointegration and ECMs with generalized quadratic ARCH-in-mean processes. The results indicate that a futures price is unbiased in the long run but may have short run pricing biases. The results support the assertion that there are short run time-varying risk premiums. Using the cointegration method and an ECM, Carter and Mohapatra (2008) study the largest non-storable commodity futures contract (Lean Hog futures) traded at the Chicago Mercantile Exchange, and their results show that a Lean Hog futures price was an unbiased predictor of a subsequent spot price during 1998 to 2004. Armah (2008) studies the cocoa futures market and finds no evidence of a constant or a time-varying risk premium. However, the author still concludes that the futures price is a biased predictor. Liu (2011) investigates market efficiency of crude palm oil futures traded in the Bursa Malaysia with Johansen cointegration test and vector error correction model (VECM). The author finds a cointegrating relationship between the futures and spot prices for all studied horizons, i.e., the unbiasedness hypothesis of crude palm oil futures price cannot be rejected.

To summarize, the overall conclusion of the literature is mixed but most studies tend to find that at least in the long run, a futures price is unbiased. However, there may be pricing biases resulting from market inefficiency or a risk premium in the short run.

4.2.2.3 Unbiasedness Hypothesis in Stock Index Futures

Antoniou and Holmes (1996) test both efficient market and unbiasedness hypotheses in the FTSE-100 futures contract. They apply an ECM and cointegration method to examine the short- and long-run relationship between spot and futures prices, respectively. They show that a futures price is an unbiased predictor of subsequent spot prices for 1- month and 2-month maturities, but not for the contracts with a longer maturity. Kenourgios (2005) uses a cointegration technique to test the unbiasedness hypothesis of the FTSE Athens Stock Exchange (ASE) and reject the joint hypothesis of market efficiency and unbiasedness. Tharavanij (2017) empirically tests the unbiasedness of futures price hypothesis in the Thai stock index futures markets. They find that in the long run, futures and subsequent spot prices move together and are cointegrated with one cointegrating vector. The results do not support the existence of a constant risk premium.

CFFEX was only founded in April 2005, and the trading on CSI 300 index futures began in April 2010. Previous studies (Kenourgios, 2005; Tharavanij, 2017) on CSI300 index futures focus mostly on detecting arbitrage opportunities or testing pricing models of futures contracts, and there is on empirical investigation on the unbiasedness hypothesis of the CSI300 index futures contract.

Table 4.1 A Review of Relevant Studies on the Unbiasedness Hypothesis

Papers	Market	DATA	Testing Methods
Tharavanij (2017)	SET50 stock index futures	Daily	ECM model
The SET50 market is efficient and the futures price is an unbiased and efficient predictor of spot price.			
Kenourgios. (2005)	ASE-20 stock index futures	Daily	Johansen's cointegration test
For Greek ASE20 market, the null hypothesis of a constant risk premium in a long run is rejected.			
Antoniou and Holmes (1996)	FTSE-100 stock index futures	Daily	variance-bounds tests
The market for the FTSE-100 stock index futures contract is efficient for one and two months prior to maturity			
Haigh, M. S. (2000)	BIFFEX futures	Daily	ECM model
In BIFFEX freight futures market, the current, one, two, and quarterly contract futures prices are unbiased and hence efficient estimators of future spot freight rates.			
Kawamoto, & Hamori (2011)	WTI futures	Daily	ECM model and GARCH-M-ECM
WTI futures are consistently efficient within 8-month maturity and consistently efficient and unbiased within 2-month maturity.			
Nikolaou & Sarno (2006),	Forward exchange rates in Foreign-exchange market	Weekly	Dynamic OLS method
Based on stationary regressions suggest that options provide biased predictions of the future spot exchange rate			
Chinn and Coibion (2013)	Futures in commodity market	Daily	GARCH model
While energy futures can generally be characterized as unbiased predictors of future spot prices, there is much stronger evidence against the null of unbiasedness for other commodities, especially for precious			

and base metals. There is not stronger evidence for unbiasedness in futures markets.

The list of relevant studies on the unbiasedness hypothesis with papers, market, data and testing model.

4.3: Data and Methodology

4.3.1 Data

All the data in this chapter are collected from the dataset introduced in Chapter 1.4.1. Table 4.2 reports the summary statistics for the return of CSI300 index futures at 1 and 2 months to maturity. Before and after the regulatory reforms, the means and standard deviations of index futures' returns are consistent. Before the regulatory change, the mean value of the daily basis data is significantly different from the intra-daily data, and the standard deviation is significantly greater than the intraday data. While after the regulations change, the standard deviation of daily data was significantly greater than other data. Intraday data of 5-min, 60-min level are similar. Therefore, the intraday data at 5-min level, 60-min level, and daily data are used in this chapter.

Table 4.2 Descriptive statistics of the CSI300 index futures return

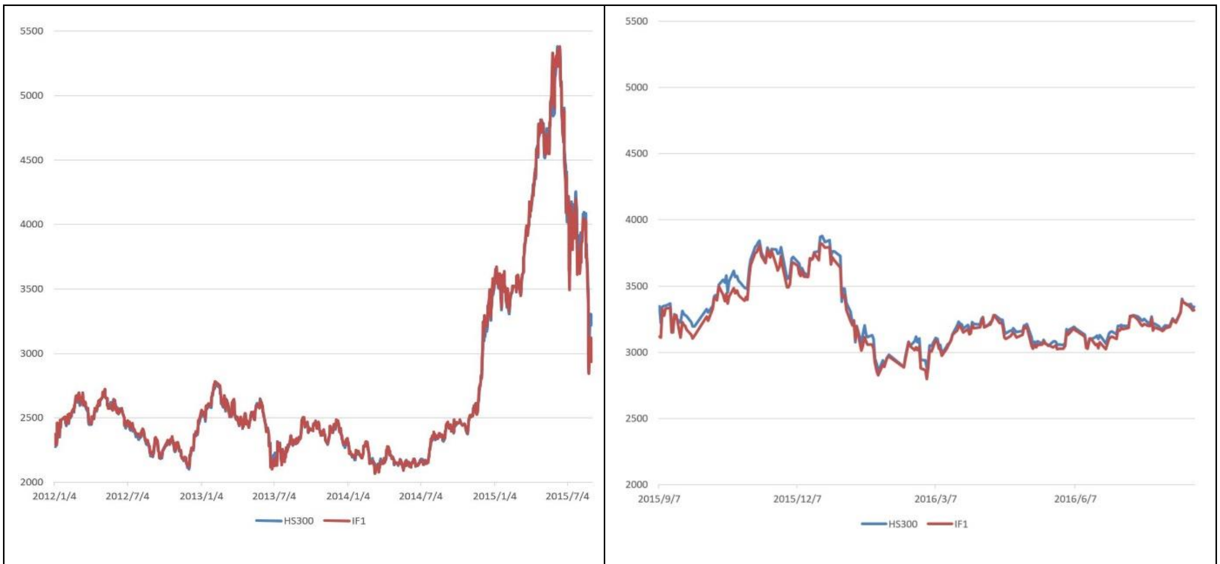
		Returns of IF1			Returns of IF2		
		BEFORE	AFTER	WHOLE	BEFORE	AFTER	WHOLE
mean	5min	5.32 e-4	4.79 e-4	5.89 e-4	4.10 e-4	7.12 e-4	5.76 e-4
	60min	5.80 e-3	5.05 e-3	5.91 e-3	4.64 e-3	8.595 e-3	5.71 e-3
	daily	0.024	0.03	0.030	0.018	0.044	0.03
Std. Dev	5min	0.27	0.20	0.25	0.27	0.22	0.25
	60min	0.79	0.78	0.79	0.82	0.80	0.82
	daily	1.88	1.82	1.87	2.00	1.94	2.00
skewness	5min	-0.11	-0.91	-0.15	-0.36	0.11	-0.19
	60min	-0.22	-0.34	-0.24	-0.37	0.20	-0.26
	daily	-0.42	-0.24	-0.36	-0.21	0.05	-0.14
kurtosis	5min	77.70	56.81	79.57	80.42	39.51	91.02
	60min	17.13	9.51	15.61	20.42	10.42	18.48
	daily	8.69	5.09	7.98	11.22	5.64	10.09
Jarque.Be	5min	9.92 e+6***	2.319 e+6***	1.511 e+6***	1.537 e+6***	1.066 e+6***	1.997 e+6***

ra	60min	37005***	2119.3***	37386***	56317***	2743***	56377***
	daily	1223***	45.30***	1186***	2506***	69.07***	2363***
Q(20)	5min	204.7***	88.19***	205.1***	172.7***	130.1***	191.2***
	60min	91.34***	26.50**	95.33***	122.1***	35.01**	130.9***
	daily	89.77***	20.84***	77.83***	91.30***	24.19*	73.07***

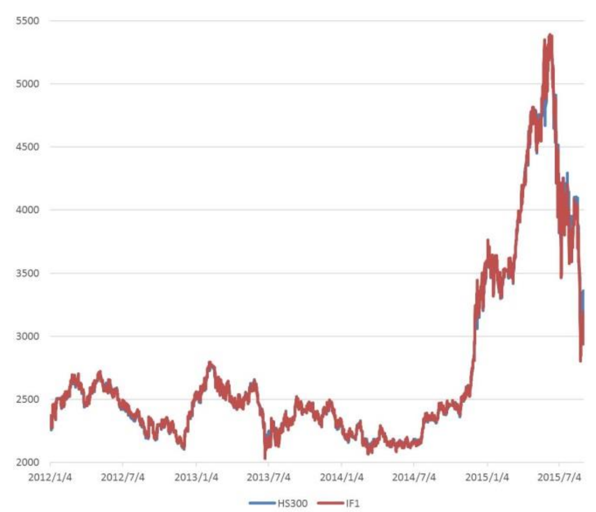
The list of statistics description for the CSI300 index futures return for IF1and IF2. $\mathrm{RF_t} = 100 * (\mathrm{IF_t} - \mathrm{IF_{t-1}})$ $\mathrm{IF_t} = \ln(\mathrm{futureprice})_t$. The definition of before, after and whole is as same as Table 2.3. *, **, and *** indicate 10%, 5%, 1% significance, respectively

After the regulatory reforms, the skewness of index futures' return changes greatly. In particular, the skewness of IF2 index futures' return has changed from a negative value to a positive value after regulatory changes. Most skewness of the index futures' returns are negative, indicating that the CSI300 stock index futures fall most of the time. It also implies that, in each time period, the increase is greater than the decline for CSI300 index futures. The value of kurtosis of index futures' return drops significantly after regulatory reforms, suggesting that average return becomes more disperse.

Figure 4.1 CSI300 Index and Index Futures Prices at IF1 (2012-2018)

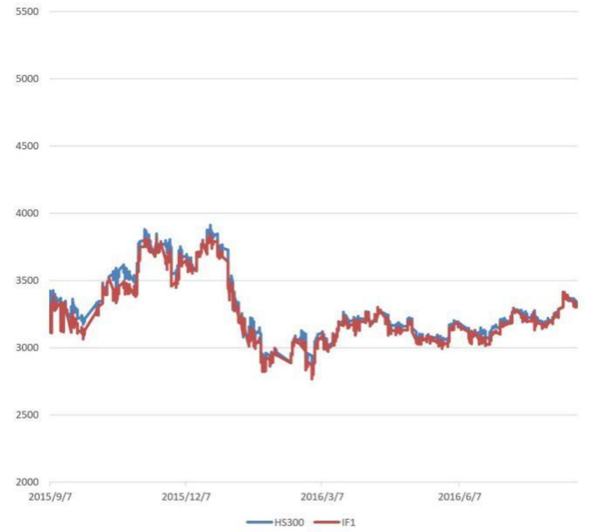


Before 03/09/2015 daily trading price | After 03/09/2015 daily trading price



Before 03/09/2015

Trading price at 5-min level



After 03/09/2015

Trading price at 5-min level

The CSI300 Index(blue lines) and Index Futures Prices(red) for IF1 with daily(upper panel) and 5min(bottom panel) sampling frequency. The definition of before(left panel) and after(right panel) is as same as Fig. 2.1.

Table 4.3 Descriptive statistics of the basis between Index price and Futures price of 1or2-month maturity

		The basis between spot and IF1			The basis between spot and IF2		
		BEFORE	AFTER	WHOLE	BEFORE	AFTER	WHOLE
mean	5min	-2.59	-28.84	-10.73	-0.29	-71.63	-22.43
	60min	-2.11	-39.47	-10.01	0.21	-96.39	-20.18
	daily	-0.44	-38.35	-8.45	1.90	-94.85	-18.53
Std. Dev	5min	33.41	29.31	34.41	52.22	49.56	61.09
	60min	32.73	33.54	36.26	51.71	50.13	64.76
	daily	33.78	34.73	37.33	52.93	51.73	65.83
skewness	5min	-3.71	-1.69	-2.60	-3.44	-1.46	-1.80
	60min	-3.49	-1.16	-2.34	-3.36	-1.17	-1.75
	daily	-3.16	-1.38	-2.20	-3.31	-1.48	-1.79
kurtosis	5min	25.67	6.15	15.82	20.11	5.03	8.05
	60min	24.09	4.56	13.18	19.43	4.44	7.17
	daily	23.13	6.52	13.39	20.32	6.51	7.97
Jarque. Bera	5min	1011800***	17118***	493720***	605100***	10174***	99190***
	60min	91399***	390.0***	29504***	58384***	374.2***	6966***

	daily	16495***	198.7***	5983***	12732***	209.1***	1761***
Q(20)	5min	744780***	338150***	1115100***	797610***	365350***	1196500***
	60min	45898***	8697***	67548***	59846***	14481***	93037***
	daily	2972***	325.9***	6111***	6300***	1166***	13810***

Notes: The list of statistic descriptions of basis between spots and futures for IF1 and IF2. Basis means Index Futures price (IFn) minus Index price (St). The definition of before, after and whole is as same as Table 2.3.

Table 4.3 shows the basis between CSI300 index and CSI300 futures price of 1 or 2-month maturity. The mean of basis appears a very significant decline after the regulatory changed. This shows that the basis between the spot and futures is very close originally, while the regulatory reforms lead to a very large basis. Large basis would affect the efficiency of index futures market.

After the regulatory changed, the skewness of basis is getting smaller in all time periods. Meanwhile, the kurtosis of basis drops down greatly. These results suggest that the fluctuations are inhibited after the regulatory reforms, which is in agreement with Fig. 4.1.

4.3.2 Methodology

This session outlines the methodologies that we used to investigate the market efficiency and unbiasedness hypothesis of CSI300 index futures, before and after the regulatory reforms.

4.3.2.1 Unit Root Tests

Stationarity of the data (in natural logs) is evaluated by the augmented Dickey–Fuller

(ADF) test, the modified Dickey–Fuller test by transforming time-series data via a generalized least squares regression (DF-GLS), the Phillips–Perron (PP) test, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test for stationarity. While the ADF, the DF-GLS, and the PP tests all state the null hypothesis of non-stationarity (a unit root), the KPSS test defines stationarity as the null. Brenner and Kroner (1995) show that if the "basis" (net cost of carry) has a unit root, then spot and futures prices will tend to drift apart, and they would not be cointegrated. In this case, the unbiasedness hypothesis cannot hold. On the contrary, if the basis is stationary, then spot and futures prices are cointegrated.

This study investigates statistical properties of spot prices, futures prices, and basis as they have implications on the interpretation from our empirical models. The above-mentioned unit root tests are performed over all key variables.

4.3.2.2 Unbiasedness Analysis

If futures price is an efficient predictor of a subsequent spot price, then both series cannot move too far away in the long term. Therefore, both series should form a cointegrating relationship. The Johansen procedure can be used to test for cointegration. The cointegrating vector would have the following form.

$$u_t = S_t - \alpha - \delta F_{t-1} \qquad (4.4)$$

u_t is the forecasting error (or in time-series parlance, the error correction term). If future price is an efficient predictor, then this error term should be stationary and white noise. F_{t-1} is the price of the futures contract that would expire at period t. The subscript means that this futures price is observed one period before the current spot price. This one period is the forecasting horizon. The futures price can be interpreted as the market forecast of the subsequent spot price at the expiry date of that particular futures contract. S_t is the spot price of an underlying at maturity date.

Efficient market hypothesis simply states that the futures price incorporates all available relevant information, concerning subsequent spot price of the underlying. Futures price can be interpreted as the market predictor of the subsequent spot price. There should be no other variables which help to predict subsequent spot price apart from its futures price. To test for market efficiency in the long run is to test that the forecasting error is stationary and white noise. Forecasting error is stationary only if subsequent spot price and futures price are cointegrated.

The above-mentioned efficiency conditions are necessary conditions but not sufficient conditions for unbiasedness of futures price. There are three cases of unbiasedness hypothesis: a zero risk premium, a constant risk premium, and a time-varying risk premium. Strictly speaking, however, it is the first case with a zero risk premium that an unbiasedness hypothesis truly holds. Cases with a constant or a time-varying risk premium are also called unbiasedness only in a sense that a futures price is still an unbiased predictor of a subsequent spot price after taking into account these risk premiums. The Johansen procedure can be used to test all hypotheses.

1) Unbiasedness hypothesis with a zero risk premium

This hypothesis states that future price is an unbiased predictor of the subsequent spot price.

If $\alpha = 0$ and $\delta = 1$, then

$$S_t = F_{t-1} + u_t \qquad (4.5)$$

The Johansen multivariate cointegrating procedure can be used to formally test the long-run unbiased hypothesis ($\alpha = 0$ and $\delta = 1$).

2) Unbiasedness hypothesis with a constant risk premium

This hypothesis states that on average, futures price is different from the subsequent spot price with a fixed proportion equal to the risk premium. Empirically, if the Johansen test could reject the null of $\alpha = 0$, but could not reject the null that $\delta = 1$, this would imply unbiasedness with a constant risk premium.

$$S_t = \alpha + F_{t-1} + u_t \qquad (4.6)$$

3) Unbiasedness hypothesis with a time-varying risk premium

This hypothesis states that on average, futures price is different from the subsequent spot price with a non-constant risk premium, which varies over time. The parameter α is not a constant over time, whereas δ still equals 1. However, it is important to note that this hypothesis cannot be directly tested in the long run because the Johansen procedure does not allow a non-constant α in the cointegrating relationship.

4.4: Empirical Results

4.4.1 Unit Root Test

The results of unit root tests on the 5-min, 60-min, and daily index futures price (1-month and 2-month maturities) are presented in Table 2.3 in chapter 2. The null hypotheses of a unit root for CSI300 index futures price of both maturities (1-month and 2-month) cannot be rejected at 5% significant level with ADF test. These confirm that CSI300 index futures price of both maturities (1-month and 2-month) are nonstationary.

Nevertheless, first differences of spot price (index) and futures price are stationary. The first difference in the research of index (spot) and index futures represents the net cost of carry or "basis", which means index futures price minus index price. In Table 4.4, Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) test statistics reject the null hypothesis at 1% significant level, implying the net cost of carry is a stationary process. The DF-GLS test however cannot reject the null hypothesis (only intraday test before regulatory reforms accept stationary) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test reject a stationary null hypothesis. It suggests that the basis of spot and futures prices do not contain a unit root, and are stationary.

Table 4.4 Unit root test of basis before and after regulatory reforms

		Basis between spot and IF1			Basis between spot and IF1		
		BEFORE	AFTER	WHOLE	BEFORE	AFTER	WHOLE
ADF	5min	-66.14***	-42.41***	-79.53***	-66.45***	-42.29***	-79.77***
	60min	-20.36***	-11.25***	-23.06***	-20.75***	-11.24***	-23.29***
	daily	-8.04***	-4.22***	-10.36***	-7.96***	-4.235***	-10.24***
DFGLS	5min	-26.70***	-3.09***	-30.42***	-35.30***	-3.27***	-40.44***
	60min	-18.72***	-1.71*	-21.86***	-20.05***	-1.48***	-23.38***
	daily	-2.912***	-6.93***	-3.28***	-3.13***	-7.57***	-3.56***
PP	5min	-42409***	-19228***	-61500***	-42798***	-19710***	-62338***
	60min	-4982***	-1144***	-6105***	-4948***	-1181***	-6112***
	daily	-826.3***	-244.6***	-1089***	-783.3***	-240.1***	-1035***
KPSS	5min	0.14	0.05**	0.08	0.14	0.06	0.07
	60min	0.13	0.10	0.08	0.12	0.10	0.08
	daily	0.12	0.10	0.08	0.12	0.10	0.07

The list of Unit root test of basis before and after regulatory reforms for IF1 and IF2 based on different models. IFn refers to Index Futures price of 1 or 2-month maturity. Basis means Index Futures price (IFn) minus Index price (St). ADF = augmented Dickey–Fuller; DFGLS= the modified Dickey–Fuller test by transforming time-series data via a generalized least squares regression; PP = Phillips–Perron; KPSS =Kwiatkowski–Phillips–Schmidt–Shin. The definition of before, after and whole is as same as Table 2.3. *, **, and *** denote 10%, 5%, 1% significance, respectively

According to Brenner and Kroner (1995), if the net cost of carry (basis) is not stationary, then cash and futures prices will tend to drift apart, and they could not be cointegrated. On the contrary, if the basis is stationary, then spot and futures prices are tied together and cointegrated. This is consistent with the implications of market efficiency and unbiasedness hypothesis.

Tharavanij (2017) and Kenourgios (2005) investigate whether the existence of stock index futures has increased positive feedback trading in emerging market, Thai stock index futures (SET50 futures) and Athens stock index futures (ASE-20 futures). To determine the order of each price series, the Augmented Dickey-Fuller test and

Phillips-Perron test are computed on the levels of each price series. Similar to the Thai stock index futures (SET50 futures), ADF and PP tests consistently reject the non-stationary null hypothesis for CSI300 index futures return. However, according to the DF-GLS test results, the null hypothesis can be rejected only at the 10% level. Correspondingly, the SET50 can reject at the level of 1%. These show that, for both CSI300 index futures and SET50 index futures in Asia emerging markets, the first difference and basis of spot and futures prices are stationary, indicating that the market is unbiased.

Kenourgios (2005) also conduct the similar tests on the Greek index futures market, their results show that the basis is nonstationary and contains a unit root. This suggests that the emerging Greek futures market is still inefficiency. The PP test is more robust to the presence of serial correlations and time-dependent heteroskedasticity. The asymptotic distribution of the PP t-statistic is the same as the ADF t-statistic. Using both ADF and PP tests, we find that the first difference and basis of spot and futures price of CSI300 are both stationary, rejecting the non-stationary null hypothesis at 1% level. However, the empirical results presented in Kenourgios (2005) suggest that the ASE-20 futures market is inefficient, and futures prices do not appear to be unbiased predictors of spot prices for one month prior to maturity of the futures contract. This has an important implication for market participants in the Greek capital market, indicating that there are opportunities for speculative profits in Greek futures market. Antoniou and Holmes (1996) investigate the FTSE-100 stock index futures market. Results show that the FTSE-100 index futures market is efficient and provides an unbiased estimate of futures' spot prices for one and two months away from expiration.

In this chapter, after performing the augmented Dickey–Fuller (ADF) test, the modified Dickey–Fuller test is also conducted by transforming time-series data via a generalized least squares regression (DF-GLS) test, Phillips–Perron (PP) test, and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. Results show that CSI300 index futures contracts of one and two months away from expiration contracts are stationary. The results of these unit root test suggest that, like other more mature futures markets, the CSI300 index futures also provides an unbiased estimate of futures' stock price.

4.4.2 Cointegration Test

Cointegration of two price series is a necessary condition for market efficiency. If the spot price and futures price are cointegrated, the two series move together and unlikely to drift apart over time. If this is the case, then the futures price is an unbiased predictor of the future spot price. Thus, the Johansen cointegration procedure (Johansen, 1988 and 1991) is employed to test for cointegration between the spot and futures markets.

Table 4.5 Johansen's cointegration test between CSI300 index and index futures price

		Trace statistic Rank=0			critical value		Trace statistic Rank<=1			critical value	
		Before	After	Whole	5%	1%	Before	After	Whole	5%	1%
IF1	5min	114.26***	102.94***	242.46***	15.67	20.20	1.38	4.66	2.06	9.24	12.97
	60min	62.39***	53.62***	105.73***	15.67	20.20	1.34	3.36	1.85	9.24	12.97

	daily	20.63***	40.44***	75.04***	15.67	20.20	1.81	2.77	2.22	9.24	12.97
IF2	5min	27.95***	52.81***	82.89***	15.67	20.20	1.70	4.77	2.13	9.24	12.97
	60min	22.87***	33.45***	43.54***	15.67	20.20	1.50	3.43	1.91	9.24	12.97
	daily	11.49	28.57***	41.04***	15.67	20.20	1.86	2.65	2.16	9.24	12.97

The list of Johansen's cointegration test results for IF1 and IF2.Note. The trace test is used to test the null hypothesis that the number of cointegrating vectors is less than or equal to rank, where rank=0(for no cointegration) or 1(for a single cointegration vector). The definition of before, after and whole is as same as Table 2.3.

In this chapter, the long-run relationship between the CSI300 index price (spot) and its futures price of 1-month and 2-months maturity are tested separately. The null hypothesis is that the number of cointegrating vectors is less than or equal to the rank, where rank is either 0 (for no cointegration) or 1 (for a single cointegrating vector). The Johansen's cointegration test results are presented in Table 4.5. The test statistics reject the null hypothesis of no cointegration between spot and futures prices. However, it could not reject the null hypothesis of a maximum of one cointegrating vector. This suggest that, before and after the regulatory reforms, both IF1 and IF2 have a cointegration relationship with the spot market and have at most 1 cointegration vector. These also indicate that the regulatory reforms in 2015 have not significantly affected the cointegration relationship between CSI300 index and its futures markets.

Using Johansen's cointegration technique, Tharavanij (2017) studies the cointegration of SET50 futures market. The result clearly rejects the null hypothesis of no cointegration between spot and futures prices. However, the null hypothesis of a maximum of one cointegrating vector could not be rejected. Their results are very similar to the findings that we documented for CSI300 futures market in this chapter.

This implies that futures price and subsequent spot prices move together over time and are unlikely to drift apart indefinitely. This is consistent with the implications of market efficiency and unbiasedness hypothesis.

The evidence presented in Kenourgios (2005) for Greek ASE-20 stock index futures market indicated that the null hypothesis of zero cointegrating vector is rejected at the 5% level, while the null of one cointegrating vector cannot be rejected. Spot price and futures price series are cointegrated, and then the first necessary condition for market efficiency is met. However, the second necessary condition for market efficiency does not hold, since the restrictions on the parameters α and b in the cointegrating relationship (α=0 and b=1) are rejected, even though the serial independence of et is accepted. Thus, the joint hypothesis of market efficiency and unbiasedness in futures prices is rejected as the two necessary conditions for market efficiency are not met, even though spot price and futures price series cointegrated. This finding is consistent with that of earlier studies on other European emerging futures markets (e.g., Martikainen et. al, 1995; Bühler and Kempf, 1995), showing the inefficiency of these futures markets.

Antoniou and Holmes (1996) examine the FTSE-100 stock index futures market. Their results show that in all cases the null hypothesis of zero cointegrating vectors is rejected at 5% level, while the null of one cointegrating vector cannot be rejected. That for 1, 2 months prior to maturity the restrictions hold at the 5% level of significance. Thus, spot price and futures price series cointegrated, and the market efficiency and risk neutrality is confirmed.

Overall, the results of our Johansen's cointegration tests suggest that, the CSI300 index futures market is largely efficient, and spot and futures price series share a long-term equilibrium relationship.

4.4.3 Vector Error Correction (VEC) and Cointegrating Vector

As there is a major a regulatory reform in the CSI300 market in 2015, in this session, we analyze the cointegrating relationship between spot and futures prices for the whole period (2012 to 2018) as well as for the two sub-periods before and after the reforms.

The Whole Period Analysis (01/01/2012 -31/12/2018)

Table 4.6 shows the Vector Error Correction Model (VECM) and Cointegrating Vector (CV) relationships between index (spot) and futures prices. The coefficients of spot price are normalized to 1. The coefficients of futures prices in cointegrating vector equations are all highly significant with negative signs as expected. For a futures price to be an unbiased predictor of a subsequent index price, the coefficient of index price must equal "−1" and the constant term equals to zero in the cointegrating vector.

Table 4.6 VECM and CV of Index Price and Futures Price of 1-month and 2-month maturity

	5min		60min		daily	
	IF1	IF2	IF1	IF2	IF1	IF2
Δs EC(-1)	-2.93 e-3*** (0.11)	-1.22 e-3* (0.14)	-1.56 e-3* (0.07)	-7.96 e-3 (0.12)	-3.62 e-3 (0.11)	1.38 e-3 (0.18)
Δf EC(-1)	3.26 e-3*** (0.13)	0.74 e-3 (0.31)	7.28 e-3 (0.11)	3.700 e-3 (0.14)	0.05 (0.12)	0.05 (0.21)
S	1	1	1	1	1	1
f δ	1.01*** (0.21)	1.02*** (0.20)	1.01*** (0.13)	1.02*** (0.15)	1.01*** (0.09)	1.00*** (0.13)
α	-7.8*** (1.78)	-17.90*** (1.82)	-8.26*** (1.41)	-17.98*** (1.73)	-8.28*** (1.37)	-17.74*** (2.28)
t test b(f)= δ = 1	55.19***	69.31632***	16.97***	20.09***	1.29	0.64
LM test at Lag1	59072***	60452***	4789***	5017***	638.4***	668.9***
LM test at Lag2	116356***	119970***	9088***	9681***	1020***	1068***

The list of VECM and CV of Index price and futures price IF2 and IF2 with different sampling frequency. “s”, “f” are index price (spot), futures price; Δs, Δf are first differences of spot and futures price, respectively. EC(−1) is a last period error correction term; the standard errors of parameters are given in parentheses. CV is a cointegrating vector with a normalized coefficient of future 1month for index price. A number in parentheses is a standard error. VECM = Vector Error Correction Model; LM test null hypothesis of no autocorrelation among VEC residuals at least up to lag 2 periods. *, **, and *** denote 10%, 5%, 1% significance, respectively.

In this study, the intraday data (5-min, 60-min prices) and daily data are analyzed. Futures and spot futures price mostly move together, the null hypothesis are accepted at 5% significant level, in respond to the error correction terms, EC(−1), in Table 4.6. This indicates that when a futures price falls below an equilibrium level with the spot price, making an error correction term positive, it will be adjusted upward towards equilibrium level in the subsequent periods. The only exception is the price change at 5-min level, the null hypothesis is rejected at 1% significant level, implying that futures and spot prices do not tend to move together.

The cointegrating relationship between spot and futures prices is reported in the "cointegrating vector" section of Table 4.6. The coefficients of spot price are normalized to 1. The coefficients of futures prices in cointegrating vector equations are all highly significant with negative signs as expected. For a futures price to be an unbiased predictor of a subsequent index price, the coefficient of index price must equal "−1" and the constant term equals to zero in the cointegrating vector. The t tests reject the null hypothesis of the coefficient of cash price being "−1" for both maturities at 1% significant level. This result implies that unbiasedness hypothesis with zero risk premium do not hold at least in the long run. Based on equation $u_t = S_t - \alpha - \delta F_{t-1}$ (4.4), the long-run unbiased hypothesis (α = 0 and δ = 1) are rejected significantly. This shows that under a long run conditions, CSI300 stock index futures are not unbiasedness with a zero risk premium. However, at the daily level, the t tests accept the null hypothesis of the coefficient of cash price being "−1" for both maturities at 5% significant level. Based on equation $S_t = \alpha + F_{t-1} + u_t$ (4.6), the Johansen test could reject the null of α = 0, but the null of δ = 1 cannot be rejected. These results imply that unbiasedness hypothesis (with a constant risk premium) holds in the long run.

From Table 4.6, δ = 1 were significantly rejected in 5-min and 60-min level. Neither futures of 1-month or 2-month maturity are statistically significant in 5-min and 60-min level. Therefore, the hypothesis of a constant risk premium in a long run is accepted only at the daily level and rejected for intraday data. While the hypothesis is rejected at both 5-min and 60-min level, the performance of 60-min data is relatively better than that of 5-min data. In general, the higher the frequency of data the worse the performance is.

The Sub-periods Analysis (Before and After the Regulation Reforms in 2015)

Table 4.7 VECM and CV of Index (Spot) Price and Futures Price of 1-month maturity before and after Regulatory Reforms

	5min		60min		daily	
	Before	After	Before	After	Before	After
Δs EC(-1)	-2.70 e-3* (0.13)	-5.27 e-3*** (0.18)	-0.02* (0.21)	-0.02 (0.13)	0.02 (0.19)	-0.08 (0.15)
Δf EC(-1)	1.82 e-3 (0.11)	3.2316 e-3 (0.12)	-0.00 (0.11)	0.02 (0.15)	0.06* (0.18)	-0.04 (0.13)
s	1	1	1	1	1	1
f δ	1.00*** (0.17)	0.99*** (0.13)	1.00*** (0.09)	1.01*** (0.11)	1.00*** (0.16)	1.01*** (0.15)
α	-2.57*** (0.47)	12.07*** (1.65)	-2.31*** (0.51)	-8.15*** (1.19)	-2.21*** (0.41)	-5.79*** (0.98)
t test b(f) = δ= 1	15.80***	-13.34***	4.69***	2.89 ***	1.89	0.92
LM test at Lag1	40419***	17869***	3733***	639.9***	363.2 ***	17.87***
LM test at Lag2	79435***	34962***	7128***	1155***	583.6***	20.25***

The list of VECM and CV for Index (Spot) Price and IF1 with different sampling frequency. "s", "f" are index price (spot), futures price; Δs, Δf are first differences of spot and futures price, respectively. EC(−1) is a last period error correction term; the standard errors of parameters are given in parentheses. CV is a cointegrating vector with a normalized coefficient of future 1month for index price. A number in parentheses is a standard error. VECM = Vector Error Correction Model, LM test null hypothesis of no autocorrelation among VEC residuals at least up to lag 2 periods. The definition of before, after and whole is as same as Table 2.3. *, **, and *** denote 10%, 5%, 1% significance, respectively.

The Johansen multivariate cointegrating procedure can be used to formally test the long-run unbiased hypothesis (α = 0 and δ = 1). There are constant terms in the cointegrating vector equation to measure a constant risk premium for each maturity. For the daily level data, before or after the regulatory reforms, δ = 1 are accepted by t-test. This shows that the CSI300 stock index futures contracts with 1- and 2-month maturity can provide an unbiasedness estimate of futures' stock prices.

In addition, the results presented in Table 4.7 also show that our results for 5-min, 60-min, and daily data remain largely consistent with one another. This in turn suggests that the regulatory reforms in 2015 do not appear to have a significant impact on the efficiency of futures market. However, for the IF1 price at 5-min level, the null hypothesis is rejected at 1% level after regulation reforms, indicating that the tighten regulations cause futures and spot price no longer move closely together at the intraday level i.e., tighter regulations have adversely affected the efficiency at the 5-minute level.

Table 4.8 VECM and CV of Index (Spot) Price and Futures Price of 2-month maturity before and after Regulatory Reforms

	5min		60min		daily	
	Before	After	Before	After	Before	After
Δs EC(-1)	-1.60 e-3* (0.13)	-2.24 e-03* (0.15)	-0.01 (0.16)	-0.01 (0.17)	0.01 (0.13)	-0.04 (0.09)
Δf EC(-1)	-0.72 e-3 (0.08)	1.57 e-3 (0.12)	-0.00 (0.11)	0.02 (0.12)	0.05 (0.14)	0.02 (0.12)
s	1	1	1	1	1	1
f δ	1.00*** (0.09)	0.94*** (0.13)	1.00*** (0.12)	1.01*** (0.15)	1.00*** (0.11)	1.00*** (0.14)
α	-3.38*** (0.52)	48.08*** (2.31)	-3.15*** (0.74)	-6.00*** (1.22)	-2.91*** (0.41)	-0.83*** (0.21)
t test b(f) = δ = 1	12.63***	-33.56***	3.81***	1.8	0.51	0.33
LM test at Lag1	41306***	18361***	3823***	711.8	334.8	31.75***

LM test at Lag2	81654***	36174***	7327***	1291	516.9	34.55***

The list of VECM and CV for Index (Spot) Price and IF2 with different sampling frequency. "s", "f" are index price (spot), futures price; Δs, Δf are first differences of spot and futures price, respectively. EC(−1) is a last period error correction term; the standard errors of parameters are given in parentheses. CV is a cointegrating vector with a normalized coefficient of future 1month for index price. A number in parentheses is a standard error. VECM = Vector Error Correction Model, LM test null hypothesis of no autocorrelation among VEC residuals at least up to lag 2 periods. The definition of before, after and whole is as same as Table 2.3. *, **, and *** denote 10%, 5%, 1% significance, respectively

As shown in Table 4.8, IF2 could not reject the null of $\delta = 1$ after regulatory changes. This result suggests that, the unbiased hypothesis holds not only for the daily next month contracts, the tighten regulations also help the 60-min level IF2 contract to become an unbiased estimate with a constant risk premium in the long run. This could be attributed to the fact that, after September 3rd 2015, the speculative traders were completely driven out of the next month contracts and most of the trading the next month contracts are initiated by the risk hedgers, which has been discussed in detail by Liu, et al (2019) and Wang (2020). The pricing bias and noise caused by the intraday speculation reduced, making the futures market informationally efficient.

Overall, our results are comparable to that of previous studies in the developing and mature futures markets. For instance, allowing for both a constant and a time-varying risk premium, Tharavanij (2017) investigate the efficiency and unbiasedness of SET50 futures with the cointegration technique and ECM. The analysis is conducted over two forecasting horizons, namely, 1 month and 2 months. The results from Johansen's cointegration test suggest that futures price and subsequent spot price are cointegrated. As such, they move together over time and will not drift apart indefinitely. Furthermore, the constant term of the cointegrating vector (for both maturities) are insignificant, rejecting the hypothesis of a constant risk premium in the long run. Their result supports the idea that the market is efficient, and the futures price is an unbiased and efficient predictor of a subsequent spot price. Overall, the results reveal that SET50 futures price is also an unbiased and efficient predictor of a subsequent spot price. Similarly, Johansen's cointegration test results of Kenourgios reject the hypothesis of a constant risk premium in a long run for the Greek ASE-20 stock index futures market.

The analysis of Antoniou and Holmes (1996) for FTSE-100 stock index futures market suggests that VEC tests are sensitive to the period over which the variances are calculated. Yet, their test results confirm a significant cointegration relationship between the spot and futures markets. They concluded that the FTSE-100 stock index futures contract is efficient for one and two months prior to maturity, but not for three months prior to maturity, and possibly not for four and five months prior to maturity.

4.5: Conclusions

4.5.1 Introduction

Theoretically, in an efficient market, the futures prices can be interpreted as market forecasts of the subsequent spot prices at the maturity of those futures contracts. Thus, market efficiency requires that futures prices will equal expected subsequent spot prices plus or minus a constant or a time-varying risk premium. In other words, futures prices should be an unbiased predictor of future spot price only if a market is efficient and there is no risk premium.

Previous investigations of this joint hypothesis relating to futures markets are not sufficient in that they either ignored the problems caused by non-stationary variables, or, if cointegration has been used, they have only considered long-run efficiency. The unbiasedness property is important because a biased forecast of a subsequent spot price would complicate the use of futures contract for hedging operations. Lence (1995) shows that an unbiased futures price is a necessary condition for the utility-free optimal hedge ratio. In addition, to analyze the impact of regulatory reforms on futures market, this chapter empirically tests the two hypotheses of market efficiency and unbiasedness for the Chinese Securities Index futures (CSI300 index futures) before and after the reforms in 2015.

The Johansen cointegration procedure is used to test for long-run market efficiency and unbiasedness while allowing for a constant risk premium. The market efficiency and unbiasedness are analyzed by a VECM. This model specification allows for both a constant and a time-varying risk premium. Testing is conducted over two forecasting horizons, namely, 1 month and 2 months, before and after the regulatory reforms.

4.5.2 Summary of Findings

Taken together, the results of our empirical tests for different CSI300 futures contracts and for different periods can be summarized as follows. First, based on the unit root test results of daily data, the efficiency of CSI300 index futures market is similar to other more mature market in the world. In addition, the Johansen's test results also suggest that the Chinese stock index futures market is efficient and that the spot and futures prices are cointegrated.

Second, for the CSI300 index futures market, the unbiasedness hypothesis (with a constant risk premium) holds in the long run. That is, the futures price is not a zero-risk but a constant risk unbiased predictor of a subsequent spot price in a long run. While the hypothesis is rejected at the intraday level (both the 5-min and 60-min data), the performance of 60-min data is slightly better than that of 5-min data. Generally speaking, the lower the frequency of data the better the performance is. Third, the impact of regulatory reforms on the efficiency of futures market does not seem to be significant. In particular, the cointegration coefficients for CSI300 spot and futures markets are almost identical before and after the regulatory reforms.

In summary, our results support the notion that the Chinese futures market is largely efficient and the futures price is a constant risk unbiased predictor of a subsequent spot price at least in a long run. It is therefore important for investors to consider carefully the information incorporated in futures prices in formulating an investment strategy. Finally, our finding that the futures market is not yet fully efficient at the intraday level indicates that there could still be an opportunity for the intraday speculative trading.

4.5.3 Suggestions for Further Research

Future research in this area can include a comparative analysis other futures contracts like single stock futures or currency futures when adequate observations can be obtained for those futures. Furthermore, additional research of a longer sample period would also be beneficial. The methodology itself could be further enhanced by including futures contracts at a higher frequent (e.g., tick by tick analysis).

Finally, the findings of Edelen et al. (2010) suggest that fluctuations in the individual retail investors' sentiment relative to that of institutional investors were the primary driver of the financial assets price for reasons unrelated to fundamentals. Exploration of the impact of such a ‘relative’ sentiment index on the Chinese futures investor behavior would be an interesting area for future research.

Chapter 5 – Conclusion

5.1 Introduction

In this thesis, we investigate the efficiency and functioning of the Chinese Security Index 300 (CSI300) index futures market. Previous researches in stock index futures markets (both mature and emerging markets) suffer from a number of empirical issues. First, there is a need to eliminate the interference caused by other financial derivatives, such as single stock futures, options and credit default swaps. Second, they need to consider potential bias caused by the shorting mechanism of the stock market. If investors with negative information could directly short in the stock market without any restrictions, it will reduce the attractiveness and appeal of trading stock index futures. Last but not least, their findings would be less convincing if the market is illiquid.

During our sample period, the CSI300 index futures is the only financial derivative in Chinese financial markets and, unlike other developed markets which need to consider the coexistence of various financial derivatives (e.g., single stock futures, options, and credit default swaps [CDSs]), it is possible to isolate the impact of stock index futures on spot price in China. Meanwhile, even the securities broker was allowed to loan stocks from clients from March 31, 2010. (SEC 2010) but due to the limited pools, loaning is very difficult in actual short selling transactions. The lack of stocks mitigates the impact of short sellers on capitalizing negative information into stock prices and therefore provides an environment to examine the influence of stock index futures' short flexibility. The CSI300 index future is one of the most liquid equity index futures in the world, total of 217 million CSI300 index futures contracts were traded, ranking fifth in global stock index futures in 2014 and increased 54.5% in 2015. For other emerging markets, illiquidity may cause bias in the empirical analysis.

In this thesis, we analyze the relationship between CSI300 futures and spot market, using a dataset of various frequency and two futures contracts of different maturity from 2012-2018. In Chapter 2, the hedging effectiveness of CSI300 index futures is examined with static and dynamic hedging methods. While a number of approaches (both static and dynamic methods) have been introduced to estimate the minimum-variance hedge ratio (MVHR), there is no consensus on the best method in computing the hedging ratio. Furthermore, as the CSI300 stock index futures have recently been introduced in 2010, it is important and informative to examine its hedging effectiveness and consider which hedging approaches would provide the most effective hedging operations in this market. Finally, given that the Chinese stock index futures market has just been launched, there is also a limited empirical research on the efficiency and informational relationship between CSI300 index and its futures market.

Using a comprehensive dataset of various frequency and different contract maturity, Chapter 3 examines the price discovery ability of CSI300 futures, and investigates whether the market is microscopically efficient. We estimate the price contribution of spot and futures markets with three widely used methodologies (PT/GG, IS, and MIS). Second, we consider the impact of regulation reforms in 2015 on the price discovery ability of the CSI300 index futures for the first time. Third, for comparison purpose, we also empirically estimate the daily price discovery measures for three other index futures on S&P 500, Tokyo Stock Price Index (TOPIX), and Financial Times Stock Exchange (FTSE) 100. The results of our analysis would help market regulators and participants in developing more effective investment and regulatory strategies.

When the stock market is in turmoil, the derivatives markets will also be affected. As the volatility of the stock market and the volume of the derivatives trading increase, when the market is under stress (that is, demonstrated by extremely large upward or downward movements), investors may become irrational and larger pricing errors may occur more frequently and persistently. In an efficient derivatives market, the futures price can be interpreted an unbiased forecast of the subsequent spot price at the maturity of that particular futures contract. In addition, to analyze the impact of regulatory reforms on futures market, Chapter 4 first empirically tests the hypotheses of market efficiency and unbiasedness of the Chinese index futures, and then examines the change (if any) in market efficiency before and after the regulation reforms in 2015.

Taken together, this thesis presents one of the first empirical investigation on the market efficiency and functions of the Chinese stock index futures and we add to the extant literature in a number of ways. Firstly, with economic globalization and the development of network information technology, the frequency and extent of fluctuations in financial markets are increasing. It is therefore necessary for financial institutions to dynamically adjust the size and proportion of their positions within the trading day (intraday). In this study, we employ both daily and intraday (60-min and 5-min) data to analyze the efficiency and functions of CSI300 futures market from 2012 to 2018, representing one of the most comprehensive transaction datasets in the literature.

Secondly, the Chinese authorities tightened the rules on trading of stock index futures in 2015 and caused the futures trading volume fall substantially, and intraday trading costs increased 100 times. These regulatory reforms provide an opportunity to study the effectiveness of stock index futures hedging under different market conditions. In particular, how will the reforms affect the hedging effectiveness of futures market? Whether regulators reforms changed the price discovery ability of stock index futures? This thesis has addressed these important questions. Finally, we also examine the hedging ratio and effectiveness of the two types of CSI300 stock index futures (i.e. continuous in the current month and consecutively in the next month contract) and compares the hedging effectiveness before and after the regulation reforms.

5.2 Summary of Findings

The results of our investigation in Chapter 2 on the hedging effectiveness of CSI300 index futures can be summarized as below. Firstly, for the daily hedging performance, the hedging effectiveness is between 73% and 85%, indicating that CSI300 index futures has the ability to hedge underlying market risks. Secondly, from the comparison of hedging effectiveness of CSI300 index futures before and after regulation reforms, we find that the hedging effectiveness drop significantly after additional restrictions were imposed in 2015. The limiting participation in stock index futures market directly led to a reduction of its hedging effectiveness and affecting the role of index futures as an effective hedging instrument. Thirdly, our evidence shows that the dynamic hedging approach (for futures contracts with different maturity) can offer a higher risk reduction. The best hedging effectiveness can be achieved at the daily level, where the performance of dynamic models (Average HE = 83%) is better than that of static models (Average HE = 76%). The dynamic hedge ratios outperform constant hedge ratios in reducing the portfolio risk, and dynamic hedging (hedge ratios are updated with the arrival of new information into the market) significantly improves the effectiveness. There are also some differences in hedge ratio and hedging effectiveness of static OLS (HE=74.32% in daily data) and VECM models (HE=77.42% in daily data). Therefore, for CSI 300 stock index futures, a simple OLS model is appropriate for static hedging. Fourth, consistent with the traditional theory, it is documented that the longer the contract expiration period, the smaller the hedging ratio (MVHR) and the lower the hedging effectiveness (HE). Finally, when comparing the performance of the 5-min and 60-min level data, we find that the daily hedging strategy appears to perform the best.

From the price discovery analysis of CSI300 index futures in Chapter 3, we have the following main findings. The results show that CSI300 index futures market contributes to the majority of share of the information, and the spot market does not play a significant role in the information discovery process. This indicates that CSI300 futures lead the spot significantly in terms of price discovery. Similar to Lien (2009), we found that price discovery takes place mostly in the futures market rather than in the spot market. Findings here suggest that the CSI300 index market and CSI300 index futures market are linked, and information is being transmitted from one market to another. Although regulatory reforms reduce the information share of CSI300 futures, CSI300 futures are still in the leading position. The intraday transaction cost has increased significantly after the reforms, decreasing the price discovery capability of CSI300 index futures and reducing the leading positions of CSI300 index futures. However, as the transaction cost of futures is still relatively lower than the stock index portfolio, the index futures continue to lead the price discovery process. With regards to the results of contract maturity, the most current month contract of CSI300 futures (IF1) tends to lead the next-month contracts (IF2) in information shares. Overall, the performance of the Chinese stock index futures is comparable to that of other more mature futures markets on TOPIX, FTSE100 and S&P500.

Finally, the results in Chapter 4 suggest that CSI300 index futures is mostly informational efficient. The daily futures price is not a zero-risk but a constant risk unbiased predictor of the subsequent spot price in a long run. The empirical result is more significant for the 60-min, rather than 5-min, level. The overall result supports the idea that the market is partially efficient and the futures price is a constant risk unbiased predictor of the future spot price at least in a long run. The regulatory reforms in 2015 does not seem to have a significant effect on the efficiency of CSI300 futures market.

5.3 Suggestions for Further Research

Overall, our findings complement to the growing literature on the relationship between futures and underlying stock market, providing evidence on the performance of a newly launched stock index futures market in China. We deem our results very important in contributing to the current debate on the role of futures market in asset pricing and volatility behavior, and are of great significance to regulators and international investors who wish to invest in the Chinese stock markets.

We suggest several directions for future research. First, the bivariate GARCH modeling method used in this paper could be extended in the multivariate framework in an effort to identify the contagion effect among the Chinese and the World financial markets. Furthermore, since a number of studies have documented the impact of derivatives (e.g., futures, option, and CDSs) on market volatility, an assessment of the impact of CSI300 index futures on the volatility of underlying stock market index would also be an interesting area for future research.

Finally, it is widely recognized that identifying and regulating specific market participants is a challenging regulatory task. Incentives, such as reduced trading fees or privileges, are often needed for traders to self-identify. How to motivate traders to produce the socially optimal level of market stability by continuing to provide liquidity via limit orders in stressful market conditions is an important topic for future research. For instance, when volatility is high, private value investors submit better-priced limit order to entice speculators to submit markets orders. When volatility increases, the market/limit order trade-off between execution speed/certainty and price increases more in favor of market orders for informed traders than uninformed traders. This differential trade-off for informed and uniformed traders raises concerns that endogenous fragility in continuous limit order books. This question represents an important area for future empirical and theoretical research.

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