Effects of Spot Market Short-Sale Constraints on Index Futures Trading*

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Abstract

We analyze the effects of spot market short-sale constraints on derivatives trading using a unique Chinese stock market futures trading database. Due to short-sale constraints, investors' pessimistic views on the underlying index can be expressed solely through short futures positions, while investors' optimistic views are dispersed through their spot and futures trading. We hypothesize that trading of pessimistic investors (with net short futures positions) contains more information than that of optimistic investors. We document the negative volatility-volume relation is associated with pessimistic investors' trading, which attenuates with less restricted spot market short-sale rules. Large pessimistic investors' net demand can predict future returns, but not the case for optimistic investors.

Key Words: short-sale constraints, volatility-volume relation, pessimistic and optimistic large investors, index futures

JEL Classification: G11, G13, C53

1. Introduction

Academics, practitioners, and regulators have long debated and studied the effects of short-sale constraints on stock prices as well as the orderly functioning of equity markets. Theoretical work can be traced back to Miller (1977) and Harrison and Kreps (1978) who show that in the presence of short-sale constraints, asset prices tend to reflect the optimistic views of the investors and prices may exceed the fundamental value of those assets. Since then, several studies have highlighted the joint effects of the short-sale constraints and heterogeneous beliefs in driving asset price bubbles and crashes (see, for example, Scheinkman and Xiong, 2003; Hong and Stein, 2003). On the empirical side, numerous studies found consistent evidence that short-sale constraints cause stock overvaluation, and the overvaluation is more dramatic among stocks that are more difficult to arbitrage (see, for example, Lamont and Thaler, 2003; Chang et al., 2007; Xiong and Yu, 2011; Stambaugh et al., 2012).

Alternatively, in the absence of restrictions, short sales promote market efficiency. For example, Bris et al. (2007) analyze cross-sectional and time-series data from 46 equity markets around the world and find evidence that prices incorporate negative information faster in countries where short sales are allowed and practiced. Boehmer et al. (2008) study order-based short sales and find that large short-sale orders are the most informative, and large informed traders buy and sell within a relatively small range of prices around the fair value of an asset, thus decreasing price volatility.

Although the literature on the effects of short-sale constraints in equity markets is extensive, little is known about how the short-sale constraints in the spot market affect trading in derivatives markets. Recently, the 2008 short-sale ban provided an opportunity for academics to examine potential impact of spot market short-sale restrictions on a specific derivatives market (e.g., options on individual financial stocks).[1] Battalio and Schultz (2011) investigate the liquidity of options on the stocks subject to this short-sale ban. In addition to finding an increase in options' spreads, they highlight the increasing importance of considering the effects of spot short-sale restrictions on related derivatives markets.

Figlewski and Webb (1993) contend that options alleviate stock market short-sale restrictions due to the fact that synthetic short positions can be created using options contracts. Furthermore, Blau and Wade (2013) show that trading of pessimistic investors shifts towards the options market from underlying stocks when short-selling of those stocks becomes more expensive. Following these two studies, we postulate that, due to short-sale constraints, investors who cannot express their pessimistic views in the spot market through short selling the underlying stocks can act on those views solely through holding net short positions in the corresponding futures market.[2] In contrast, investors with optimistic views of the spot market may dilute the value of their information by holding long positions in either (or both) spot and futures markets. Hence, net short futures positions taken by traders with pessimistic views are expected to be relatively more informative than the net long futures positions taken by traders with optimistic views.

Our paper explores, for the first time, the effects of spot market short-sale constraints on futures market, specifically on the trading of stock index futures contracts. For this purpose, our empirical methodology utilizes the volatility-volume relation and the return predictability of investors with different spot market sentiment. Daigler and Wiley (1999) argue that the

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[1] The Securities and Exchange Commission (SEC) Rule 204T banned the short sales of certain financial stocks between September 19 and October 8, 2008.

[2] This is true as long as there are no options contracts or shortable exchange-traded funds (ETF) contracts available on the underlying equities, which is the case for our empirical analysis.

volatility-volume relation varies with the amount of information investors possess. While informed investors trade around the intrinsic value of assets and their trades are expected to reduce the price volatility, uninformed or less informed traders may exaggerate price changes and increase volatility. Therefore based on our hypothesis, we expect that trading by investors, especially the ones holding large positions, with pessimistic views of the spot market is more likely to be negatively correlated with futures volatility than trading by those with optimistic views. In addition, the positions of the pessimistic investors are expected to predict future returns better than those of optimistic investors.

We test our hypotheses using the daily trading data for the CSI 300 Index futures traded at the China Financial Futures Exchange (CFFEX). China is ideal for testing our hypotheses for the following reasons. First, short selling in the Chinese stock markets has explicit restrictions, with a limited number of stocks under a pilot program allowed for short-selling.[3] In particular, since the introduction of the CSI 300 Index futures in 2010, the short-sale pilot program has been expanded twice, offering us an opportunity to investigate the effects of variations in the degree of short-sale restrictions. Second, the CFFEX has disclosed the daily trading volume and positions of the largest 20 trading firms, which we refer to later as large investors.[4] The detailed daily disclosure data allows us to identify the pessimistic versus optimistic views of the large investors and track the different effects of their trading. The orderly relaxation of short-sale restrictions as well as the existence of only a single type of derivatives on the stock market provide us cleaner tests compared to the 2008 short-sale ban. Grundy et al. (2012) indicate that 2008 short-sale ban is "implemented as a response to unusual market conditions." Battalio and Schultz (2011)

[3] See the detailed discussion in Section 2 and 3.

[4] Anecdotally, the daily disclosure is intended to discourage potential excessive speculation in the CSI 300 Index futures contracts by large investors, and only the largest 20 trading firms are disclosed.

highlight the extensive regulatory uncertainty throughout the entire duration of this unprecedented event.[5]

Our findings are as follows. We show that the negative volatility-volume relation is mostly associated with the trading by pessimistic investors, the group of the large investors holding net short positions in the index futures contracts. In contrast, trading by large investors with optimistic views exhibits no significant effect on futures volatility. After the expansion of the short-sale pilot program (i.e., as short selling becomes less restricted), we find that the effects of pessimistic investors' trading weakens in terms of decreasing volatility.

By further analyzing the daily disclosure data of the large futures trading firms, we document varying effects of different types of exchange membership on the volatility-volume relation. The negative volatility-volume relation is more pronounced for the activity of pessimistic trading members who can only transact for their own accounts. Activity of clearing members, who can transact for both their own and client accounts, does not appear to be as informative. This finding suggests that the activity of pessimistic trading members is relatively more informative than those of the optimistic trading members as well as both the pessimistic and optimistic clearing members.

Lastly, we provide further evidence on the informativeness of the pessimistic and optimistic large investors' trading activity by investigating the return predictability of their net futures positions. We find that the net position of large pessimistic investors is able to correctly

[5] Battalio and Schultz (2011) state that "the short sale ban, which was to take effect immediately, was announced in the early morning hours of September 19 with no prior warning to market participants. Numerous officials of the options exchanges, some of whom we cite, complained that the ban resulted in great uncertainty both about how the ban was to be implemented and about possible additional regulation."

predict future returns within a week, and this prediction is mainly significant for the pessimistic trading members.

Our study contributes to the literature by providing new evidence for the effects of spot market short-sale constraints on the trading behavior and asset prices in the derivatives markets. For example, Battalio and Schultz (2011) and Grundy et al. (2012) focus on the effects of 2008 short-sale ban on the equity option markets in the US.[6] McMillan and Philip (2012) study the spot and futures cross-market efficiency implications of the short-selling constraints imposed in nine countries during the financial crisis, and find that arbitrage is less effective during the ban period. They focus on the pricing relationship between the spot equities and futures contracts on those individual stocks. We take a different approach by looking at how the spot market short-sale constraints affect the relative informativeness of the activity by pessimistic versus optimistic futures traders. We provide the first evidence in the literature that the negative volatility-volume relation in futures markets is mostly associated with the trading of pessimistic investors, and this negative relation weakens as spot market short-selling gets less restricted.

Our study also sheds light on the literature of the informational efficiency of short sales. On one hand, there are a good number of studies showing that constrained short sales are detrimental for market efficiency. For example, Beber and Pagano (2013) find that short-sale bans decrease stock liquidity and slow price discovery. Boehmer et al (2013) document large-cap stocks subject to the ban suffered a severe degradation in market quality. Boulton and Braga-

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[6] Although analysis of Grundy et al. (2012) consider the single stock futures and ETFs in addition to options, these potential alternative derivative markets have extremely low liquidity before and during the short-sale ban. In addition, the authors conclude that “short-sale ban acts as an effective restriction on trading in options”. Therefore, we believe that our extension of this line of inquiry is well warranted and our research makes significant contribution to the literature in part because our results are not affected by various confounding forces.

Alves (2010) also find the restrictions negatively impact various measures of liquidity. On the other hand, many studies, such as Jarrow (1980), Figlewski (1981), Diamond and Verrecchia (1987), and Chen et al. (2002), present mixed results. For example, Diamond and Verrecchia (1987) show that short-selling bans reduce the speed of price discovery, but the effect on the bid-ask spread is ambiguous. Our study adds new evidence to the literature of information efficiency with a set of particularities for the Chinese equity markets, such as the gradual removal of short-sale restrictions and the transparency in the identification of trading positions. We show that as the short-sale restriction is lifted, the information advantage of traders with net short positions in the futures market gradually weakens, indicating that part of the information contained in the trading activities of pessimistic investors gets incorporated into the underlying markets. Consistent with our conjecture, studies focusing on the effects of short-sale regulations on Chinese stock markets, such as Chang et al. (2014), show that stock price efficiency increases after the short-sale ban is lifted. The implication is that unrestricted short sales improve market efficiency, and markets should favor unrestricted shorting rules.

The rest of the paper is organized as follows. Section 2 discusses the related literature and testable hypotheses. Section 3 describes the data and institutional details, followed by a description of the construction of our trading and position variables and volatility estimates in Section 4. Section 5 presents our empirical analysis and findings. Section 6 concludes.

2. Related Literature and Testable Hypothesis

We investigate the effects of spot market short-sale constraints on the futures market volatility-volume relation and the return predictability of trading by investors with different spot-market sentiment. The volatility-volume relation has been studied within various theories and models. The dispersion of beliefs and information models proposed by Harris and Raviv (1993) and Shalen (1993) suggest that the volatility-volume relation depends on who is generating volume and how much information they perceive. Informed traders buy and sell within a relatively small range of prices around the fair value of the assets and hence their trades decrease the price volatility. While uninformed (or less-informed) traders are likely to react to all changes in volume and price as if they reflect information, hence they tend to exaggerate price movements and result in greater price variability. The volatility-volume relation has also been analyzed in complementary rather than competing theories and models. For example, the mixture of distribution hypothesis (Clark, 1973; Harris, 1986; Tauchen and Pitts, 1983) assumes that the number of information arrivals causes the joint distribution of volatility and volume. In this paper, our goal is not to distinguish between the different theories driving this volatility-volume relation; instead, we use the volatility-volume relation framework to identify the relative informativeness of trading by futures markets participants with different spot market sentiment and to investigate the effects of spot market short-sale constraints on futures markets.

To do so, we focus on the Chinese equity markets where the existence and changes of the spot market short-sale restrictions provide a unique opportunity for our study. Short selling has explicit and implicit constraints in the Chinese equity markets with approximately 2,000 stocks listed for trading. Short-selling was completely banned prior to March 31, 2010. The China Securities Regulatory Commission (CSRC) then initiated a pilot program allowing short-sale of 90 selected stocks by qualified investors. Stocks selected for the pilot program had to meet certain criteria based on size, liquidity, and volatility.[7] The requirements for qualified investors,

[7] More specifically, a firm must have no fewer than 200 million tradable shares and a public float no less than RMB 800 million. The number of shareholders must be no fewer than 4,000. In any given day during the past three months, the daily turnover must be no lower than 15% of index turnover, the daily trading value must be no lower than RMB 50 million, its average return must not deviate more than 4% from the index return, and its return

differing across security and brokerage firms, place implicit constraints on short-selling in this limited scale (see Chang et al., 2014). Furthermore, Stambaugh et al. (2012) argue that short-sale impediments in stock markets exist implicitly due to institutional constraints, arbitrage risk, behavioral biases of traders, and trading costs.

During our sample period, options contracts or domestic shortable exchange-traded funds (ETFs) were not available for investors to trade in Chinese financial markets.[8] Therefore, the existence of only stock index futures eliminates the confounding effects of alternative derivatives with differential liquidity, a concern in the studies focusing on the 2008 short-sale ban described earlier.

As a result of the spot market short-sales restrictions, investors can only express their pessimistic views of the stock market through taking short positions in the index futures market, while optimistic views of investors can be dispersed between the spot and futures markets as they hold long positions in either or both markets. Note that investors can hold a long position in the spot markets through purchasing index mutual funds or ETFs, which make it relatively easier holding the long positions than holding short positions in the spot markets. Therefore, we expect that the trading of the pessimistic large investors in the index futures contract is relatively more informative than that of the optimistic investors, producing a stronger negative effect on futures return volatility. Therefore, the main hypothesis of our paper is:

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volatility must be no higher than five times of the index volatility. Among all the companies eligible for short-selling, the CSRC randomly selected 90 firms in the initial pilot program. Similar criteria was applied when the CSRC expanded the pilot program in 2011 and 2013.

[8] Although domestic ETFs existed during our sample period, there were no inverse ETFs which could be traded to act on a pessimistic market view of the market, and short selling of domestic ETFs were not permitted.

HYPOTHESIS 1. Due to short-sale restrictions, trading of large investors with pessimistic views of the spot market is more likely to be negatively correlated with return volatility of the futures contracts than trading by those with optimistic views.

During our sample period, the short-sale pilot program has been expanded twice, on December 5, 2011 and on January 31, 2013, increasing the number of stocks available for short-selling. We are able to use the variations in the degree of short-sale restrictions as a natural experiment to further test our hypothesis. We expect that the negative volatility-volume relation of the pessimistic investors' trading weakens as more stocks can be short-sold in spot market, these investors can now act on their pessimistic views in both the futures and underlying spot markets. However, due to the limited scale of the pilot program and the implicit short-sale constraints described by Stambaugh et al. (2102), we do not expect this negative relation to disappear. Hence, our second hypothesis is:

HYPOTHESIS 2. The negative volatility-volume relation of the pessimistic investors' trading attenuates as short selling gets less restricted.

To further investigate the effects of spot market short-sales restrictions on the stock index futures trading, we examine the return predictability of net positions of both the pessimistic and optimistic large investors. Return predictability in the futures market has been widely explored in the literature. For example, Wang and Yu (2004) analyze the daily price, volume, and open interest data on 24 futures contracts traded in the United States. They find that in addition to historical prices, lagged trading volume and open interest correlate significantly with future price changes. Wang (2004) investigates the relation between trading volume and return predictability in currency futures and finds that trading strategies are profitable when contrary to the position changes of hedgers but consistent with those of speculators. We expect that trading by large investors with pessimistic views of the underlying spot market who cannot act on their views in spot market due to short-sale restrictions, would better predict returns in the futures prices. Consequently, our third hypothesis is:

HYPOTHESIS 3. Due to the short-sale restrictions in the spot market, the pessimistic large investors' positions (net-demand) in futures market are more informative in predicting future returns.

3. Data and Institutional Background

3.1 Data and Regulations in the Chinese Markets

The data used in our study are the CSI 300 Index futures contracts traded in the China Financial Futures Exchange (CFFEX). The CSI 300 Index is a market capitalization weighted index of 300 A-shares stocks listed in China's two stock exchanges, the Shanghai Stock Exchange and the Shenzhen Stock Exchange. The CFFEX was established in Shanghai on September 8, 2006, and within two months it launched the CSI 300 Index futures mock trading system, which was modified in 2007. Actual trading of the CSI 300 Index futures contract formally started on April 16, 2010. CSI 300 Index futures contracts trade in monthly cycles: current month, next month, and next two calendar quarters (a total of four contracts).

We obtained the top 20 large trader volume and position data for the CSI 300 Index futures contracts from the CFFEX. At the end of each trading day, the exchange discloses on its website the identities of firms whose trading volume, long positions, or short positions rank them within the top 20 largest trading firms on that day, together with each firm's actual volume, long and short position values.[9]

The CFFEX uses a multi-tiered clearing system, comparable to those used by many overseas markets, that divides exchange members into different tiers in accordance with their tolerance to risk. Members in different tiers have different business scope which enables to construct a multi-tiered risk control system to hedge risks efficiently and to improve the exchange's overall risk control capability.[10] The first tier of this system divides exchange members into two categories: clearing members and non-clearing members. Non-clearing members engage in proprietary trading and/or brokerage business but are not allowed to do the clearing directly with the exchange. Exchange's clearing membership group is further divided into three member categories: trading-clearing, general-clearing and special-clearing. The special-clearing members can only engage in clearing and settlement for non-clearing members. The trading-clearing members are only eligible to trade and engage in clearing and settlement for their own accounts while the general-clearing members are allowed engage in all three activities for both their own accounts and for non-clearing members. We have obtained the exchange membership directory containing the identities and classification of member firms and our dataset of the daily top 20 largest trading firms consists of trading-clearing members and general-clearing members.

In addition to the unique and detailed disclosure data, we also obtained the daily futures settlement prices, trading volume and open interest data for all contract months from the CFFEX. Our intraday data for the CSI 300 Index futures contract is collected from the Bloomberg

[9] CFFEX only discloses for the top 20 largest trading firms ranked by their trading volume and positions, and such detailed information is not disclosed for the rest of the trading firms.

[10] This information is available from the CFFEX website: http://www.cffex.com.cn/en_new/gyjys_6434/jyjg/.

Professional terminal. For each trading day, we recorded the open, high, low, close prices as well as the number of contracts traded for each 1-minute interval. Our sample period is from the launch date of the CSI 300 Index futures, April 16, 2010 to November 15, 2013 for our intraday and daily data.

Two weeks before the launch of the CSI 300 Index futures, on March 31, 2010, the China Securities Regulatory Commission's (CSRC) initiated a pilot program for short-selling of 90 stocks (50 stocks listed in the Shanghai Stock Exchange and 40 stocks in the Shenzhen Stock Exchange). All of the 90 stocks were members of the CSI 300 Index on that day. During our sample period, the short-sale pilot program has been expanded twice, on December 5, 2011 and on January 31, 2013. Table I presents the details of the expansion of the short-sale pilot program. On December 5, 2011, the CSRC increased the number of stock allowed for short-selling to 278, of which 260 stocks were members of the CSI 300 Index on that day. On January 31, 2013, total number of stocks allowed for short-selling under the pilot program was increased to 500 and this list contained all of the 300 members of the CSI Stock Index on that day. We have obtained the names and index weights of all stocks in the CSI 300 Index on each of the above dates from the Bloomberg Professional terminal and calculated the proportion, based on market capitalization, of the CSI 300 Index stocks which were allowed to be short-sold under the pilot program. The stocks in the short-sale pilot program counted for 63.8% of the value of CSI 300 when the index futures trading started on April 16, 2010; this proportion increased to 96% and to 100% of the value of the index on December 5, 2011 and on January 31, 2013, respectively. Expansion of the pilot short-sale program provides us a unique setup in testing of our hypothesis as short-sale restrictions are explicitly relaxed for the stock in the CSI 300 Index.[11]

[11] Note that our main variables of interest, the pessimistic and optimistic volume, are the trading volumes of the index futures contracts, variables that are not derived specifically from stocks in the pilot program. Our empirical

3.2 Related Foreign Financial Products

Although short sales in the Chinese markets are restricted, foreign ETFs on the China region (e.g., FXI, MCHI, and CHIX) existed during our sample period, and large institutional investors could have resources to short them in foreign markets. Institutional investors could also achieve short positions through trading inverse and leveraged ETFs (e.g., YANG, YXI, YINN, and XPP) or shorting Chinese American depositary receipts (ADRs) traded in foreign markets. However, we believe there are at least two reasons why these foreign products may not affect our main findings regarding the information advantage of large traders holding net short positions in the futures market.

First, only a small number of Chinese institutions can invest in foreign financial markets, and such investments are highly regulated. During our sample period, there were a total of 58 institutions that fall into what the Chinese regulators classify as "Qualified Domestic Institutional Investors", who are allowed to invest in foreign securities. Among these qualified institutions, only seven of them have sub-companies that trade the CSI 300 Index futures contract. Furthermore, three of the seven sub-companies trade futures occasionally (e.g., appearing in the top-20 lists less than one third of the trading days). Comparing to the total number of 145 trading firms appearing in the top-20 list, the aggregate effect of shorting foreign financial products on the CSI 300 Index futures trading tends to be limited.

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analyses of the index futures trading are more related to the relative restrictive level of the short-sale regulations (e.g., expanding the short-sale list from 90 to 260 stocks in the CSI 300 Index), and less sensitive to which stocks were selected for the short-sale pilot program. So we believe the stock selection criteria for the pilot program should not lead to endogeneity issues in our empirical design, and neither should it have a major impact on our empirical findings.

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Second, the existence of alternative foreign financial products could lead to no significant effect of the net short positions in the stock index futures contract because pessimistic investors could also express their negative opinions by shorting foreign products in which the underlying assets are from the Chinese equity markets. But even with the potential information dilution resulting from large investors taking short positions in foreign markets, we are still able to document a significant negative effect of the pessimistic opinions on futures volatility (see Section 5). Therefore, the relative information advantage of pessimistic versus optimistic large investors in the futures market could not be (totally) eliminated by the information dilution caused by trading in foreign financial products. The existence of the related foreign financial products and trading of those products would not affect our main conclusions.

4. Variable Construction

4.1 Pessimistic versus Optimistic Volume and Position Variables

We first focus on trading volume of the top 20 largest traders, and classify them as pessimistic versus optimistic traders based on their net positions.[12] The non-top 20 investors are classified as small traders:

- *Optimist-Volume*: is the sum of trading volumes of the top 20 largest investors whose long futures position is greater than (or equal to) their short position—investors with net long position—at the end of previous trading day.

[12] In our empirical analysis we use the natural log of volume and position variables (measured in number of contracts).

- *Pessimist-Volume*: is the sum of trading volumes of the top 20 largest investors whose long futures position is smaller than their short position—investors with net short position—at the end of previous trading day.[13]
- *Small-Volume*: is the trading volume by non-top 20 investors, which is calculated as the total futures trading volume minus the sum of *Optimist-Volume* and *Pessimist-Volume* on the same trading day.

Next, we categorize the net demand of the top 20 largest investors based on the difference in their long and short futures positions at the end of a trading day:

- *Optimist-Net-Demand*: total long positions minus total short positions of the top 20 largest investors whose long futures position is greater than (or equal to) their short position, i.e. traders holding net long position at the end of a trading day. In our empirical analysis, we use the scaled net-demand value, dividing the *Optimist-Net-Demand* by the total open interest at the end of each trading day.
- *Pessimist-Net-Demand*: total long positions minus total short positions of the top 20 largest investors whose long futures position is less than their short position, i.e. traders holding net short position at the end of a trading day. Again, we scale the *Pessimist-Net-Demand* by the total open interest at the end of each trading day in our analysis.

We further partition our pessimistic and optimistic volume and net-demand variables for the top 20 largest investors based on their exchange member classification. Since our disclosure

[13] We use the sum of volumes to capture the aggregate information content of pessimists versus optimists. Sum of the trading volumes have been used in the literature to study the information effects of the different types of traders on the volatility-volume relation (e.g., Chen and Diagler 2000 and Daigler and Wiley 1999). In Section 5.3, we also discuss results based on alternative volume measures to address the potential bias caused by the actions of one or two large trading firms.

data is for the top 20 largest members, it is not surprising that we do not observe non-clearing members or special clearing members who, by classification, are expected to be smaller in general.

In our analysis, *Trading Members* refer to those firms classified by the CFFEX as trading-clearing members, because they are only eligible to trade and engage in clearing and settlement for their own accounts. Similarly, we refer to the general-clearing members as *Clearing Members*, because this group of firms can trade, clear and settle futures contracts for both their own accounts and for non-clearing members. Since our disclosure data do not break down the volume and positions of the clearing members for own-account vs. customer accounts, we expect that the trading members' activities to be more informative, due to the fact that a clearing member and its various clients may have opposing views and motivations leading to noisier volume and position values.

Then we classify the volume and position variables for pessimistic large investors as *Trading Member Pessimist-Volume, Clearing Member Pessimist-Volume, Trading Member Pessimist-Net-Demand and Clearing Member Pessimist-Net-Demand*. For example, *Trading Member Pessimist-Volume* is the sum of trading volumes of the top 20 largest firms classified as *Trading Members* and whose long futures position is less than their short position—investors with net short position—at the end of previous trading day. The corresponding volume and net-demand variables for optimistic large trading firms are classified similarly in our analysis.

Finally, we define two time serial dummy variables to capture the changes in the short-sale restrictions during our data period:

- *D2011*: an indicator of the time period before or after December 5, 2011, which takes the value of 1 if trading day is on or after December 5, 2011 and value zero otherwise.

- *D2013*: an indicator of the time period before or after January 31, 2013, which takes the value of 1 if trading day is on or after January 31, 2013 and value of zero otherwise.

We are particularly interested in the coefficients of the interaction terms of the short-sale restrictions dummies and volume variables. The first expansion of the pilot program in 2011 results in a change in spot short-sale restrictions on the CSI 300 Index by 32.2% (= 96.0% - 63.8%), which is larger than that caused by the second expansion (4% = 100% - 96%). Therefore, we expect that the impact of changes in spot short-sale restrictions on the CSI 300 Index futures trading to be larger and more prominent in 2011 than that in 2013 (regarding the coefficients of interaction variables for *D2013*).

4.2 Volatility Estimation

We estimate the unconditional return volatility based on intraday 1-minute intervals using four different measures to provide robust empirical results. First, we calculate the absolute value of returns for each minute in a trading day, which is a simple measure of unconditional volatility. Forsberg and Ghysels (2007) show that this volatility measure predicts the quadratic returns very well.

Second, we use a reduced form of the volatility measure developed by Garman and Klass (1980). In our analysis, this measure is based on intra-minute price ranges:

$$Volatility_{m,t} = \{0.5 \times [\ln(High_{m,t}) - \ln(Low_{m,t})]^2 - [2\ln(2) - 1][\ln(Open_{m,t}) - \ln(Close_{m,t})]^2\}^{1/2} \qquad (1)$$

where $High_{m,t}$, $Low_{m,t}$, $Open_{m,t}$, and $Close_{m,t}$ are the high, low, open, and closing prices of the CSI 300 Index futures at each minute *m* of day *t*, respectively. Garman and Klass (1980) compare the relative efficiency of several volatility measures, and conclude that their proposed measure provides the highest efficiency.[14]

Next, we utilize the unconditional volatility measure proposed by Rogers and Satchell (1991). One of the assumptions of range-based volatility estimations, such as the Garman-Klass (1980) measure, is that prices follow random walk with zero drift. Rogers and Satchell (1991) suggest that intraday prices may contain a drift component and propose a volatility estimate model which is drift-independent:

$$\begin{aligned} Volatility_{m,t} = \{ & [\ln(High_{m,t}) - \ln(Open_{m,t})][\ln(High_{m,t}) - \ln(Close_{m,t})] \\ & - [\ln(L_{m,t}) - \ln(Open_{m,t})][\ln(L_{m,t}) - \ln(Close_{m,t})]\}^{1/2} \end{aligned} \tag{2}$$

Finally, we include the simple range-based volatility estimate of Parkinson (1980):

$$Volatility_{m,t} = \{[\ln(High_{m,t}) - \ln(Low_{m,t})]^2 / [4\ln(2)]\}^{1/2} \tag{3}$$

After calculating the above volatility measures for each 1-minute time interval, we use the median of 1-minute volatilities for each day as our measure of volatility under each method.[15]

Table II presents the summary statistics for the futures returns, volatility estimates, and the pessimistic and optimistic volume and net-demand variables. Over the entire sample period, the average of future returns is negative, with the standard deviation of 1.45%.[16] The disclosed trading volume and net demand of large pessimistic investors have similar magnitudes as those of the optimistic investors in the CSI 300 Index futures contract. Figure 1 shows that over our sample period the Chinese stock market declined as measured by the spot level of the CSI 300

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[14] The Garman-Klass volatility measure has been widely used in various studies of futures return volatility; for example, see Daigler and Wiley (1999) and Wang (2002).

[15] Using the average of 1-minute volatility for each day yields similar results.

[16] We test whether futures returns follow a unit root process using Dickey and Fuller (1979), and we reject the null hypothesis at 99% confidence level.

Index, while the spot trading volume did not have a consistent upward or downward trend. *Clearing Members* in general exhibit larger trading volume than *Trading Members*, which is also true when we separate the volumes by pessimists and optimists. A similar pattern is observed regarding the net demand of the different member types. We also see in Table II that the mean intraday 1-minute based volatility estimates derived from the four measures have similar magnitudes. The Garman-Klass measure has the largest mean of 0.079% and the largest variation of 0.025%.

5. Empirical Analysis

5.1 Short-Sale Restrictions, Investor Trading and Index Futures Volatility

Using the four different daily intraday 1-minute based measures of futures return volatility—*Absolute Return*, *Garman-Klass*, *Rogers-Satchell*, and *Parkinson*—we investigate our first hypothesis of the effects of short-sale restrictions on volatility-volume relation of investors with pessimistic versus optimistic views (*Optimist-Volume* and *Pessimist-Volume*):

$$\begin{aligned} Volatility_t = \alpha &+ \beta_1 Pessimist\text{-}Volume_t + \beta_2 Optimist\text{-}Volume_t + \beta_3 Small\text{-}Volume_t \\ &+ \beta_4 Volatility_{t-1} + \beta_5 Volatility_{t-2} + \beta_6 Open\ Interest_t \\ &+ \beta_7 \Delta Total\ Trading\ Volume_t + \varepsilon_t \end{aligned} \tag{4}$$

where $Volatility_t$ represents either *Absolute-Return*, *Garman-Klass*, *Rogers-Satchell*, or *Parkinson* estimates, and $Small\text{-}Volume_t$ is defined in Section 4.1. Following Bessembinder and Seguin (1992; 1993) and Chan and Fong (2000), our model includes $Open\ Interest_t$ and change in the daily total trading volume ($\Delta\ Total\ Trading\ Volume_t$), which according to these studies, are potentially correlated with the trading activities of informed traders. Additionally, 1- and 2-day lagged volatilities (*Volatility*$_{t\text{-}1}$ and *Volatility*$_{t\text{-}2}$) are included to control for the persistence in volatility.[17]

For all the regressions of the daily intraday 1-minute based volatility measures, we use ordinary least squares (OLS) estimations with *t*-statistics calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors with optimal lag specification based on the Akaike information criterion (AIC).

Our estimation results are presented in Panel A of Table III.[18] When we use *Absolute Return* as the estimate of unconditional volatility in Column 1, we find that trading by large investors with pessimistic views of the underlying spot market (*Pessimist-Volume*) is negatively correlated with the futures return volatility at the 1% significance level, while the trading by large investors with optimistic views (*Optimist-Volume*) is not significantly correlated with volatility. Column 2 shows that when we use the *Garman-Klass* volatility estimate, trading by large investors with pessimistic views of the spot market (*Pessimist-Volume*) decreases futures return volatility significantly, while the trading by large investors with optimistic views (*Optimist-Volume*) does not have a significant effect on volatility. Note that the economic significance of the negative effect of *Pessimist-Volume* on *Volatility* is large. For example, a one standard deviation increase in *Pessimist-Volume* could decrease the volatility *Garman-Klass* by 25.9% (= 0.0094 × 0.688/0.025) of its standard deviation. The results using volatility measures of *Rogers-Satchell* (Column 3) and *Parkinson* (Column 4) are very similar to those using the *Absolute Return* and *Garman-Klass* estimates. We document both a statistical and an

[17] Since we detect persistence in daily intraday 1-minute based volatility measures, models include all the significant lags (i.e., the first two lagged volatilities).

[18] Panel B of Table III presents results using Generalized Linear Models estimation which we refer to in our discussion of robustness in Section 5.3.

economically significant negative volatility-volume relation of the *Pessimist-Volume*, but no significant relation with the *Optimist-Volume*.

These results support with our first hypothesis that due to short-sale restrictions, trading by pessimistic large investors is relatively more informative than that of the optimistic large investors. The results hold after controlling for the level of open interest, changes in market-wide trading and persistence in volatility.

Moreover, we find that the trading by small investors is significantly positively correlated to the return volatility of the CSI 300 index futures, a finding which is uniform across all measures of volatility. This is consistent with the argument in Daigler and Wiley (1999) that small investors are more likely to trade as noise traders, and their trading exacerbates price movements and is associated with higher volatility.

5.2 Impact of Changes in Short-Sale Restrictions on Trading and Index Futures Volatility

We further investigate the impact of spot short-sale restrictions on the relationship between index futures volatility and trading volume of pessimistic and optimistic large investors. We use the variations of the degree of short-sale restrictions and incorporate two time-serial dummy variables following the regulation changes of the short-sale rules. We estimate the following model:

$$\begin{aligned} Volatility_t = {} & \alpha + \beta_1 Pessimist\text{-}Volume_t + \beta_2 Optimist\text{-}Volume_t + \Sigma_{j=1}^{2}\gamma_j Dummy_{jt} \\ & + \Sigma_{j=1}^{2}\theta_j Pessimist\text{-}Volume_t \times Dummy_{jt} + \Sigma_{j=1}^{2}\eta_j Optimist\text{-}Volume_t \times Dummy_{jt} \\ & + \beta_3 Small\text{-}Volume_t + \beta_4 Volatility_{t-1} + \beta_5 Volatility_{t-2} + \beta_6 Open\ Interest_t \\ & + \beta_7 \Delta Total\ Trading\ Volume_t + \varepsilon_t \end{aligned} \tag{5}$$

where $Dummy_{jt}$ variables are $D2011_t$ and $D2013_t$ as defined in Section 4.1, and the rest of the variables are defined similarly as in equation (4).

Our main variable of interest is the interaction term of *Pessimist-Volume* and *D2011*. Since short-sale restrictions have been alleviated on a larger scale after December 5, 2011, we expect the negative volatility-volume relation to be weaker, which is equivalent to a positive coefficient of *Pessimist-Volume*×*D2011*. Panel A of Table IV reports the results incorporating the short-sale restrictions dummy variables.

Consistent with our Hypothesis 2, we find a significant positive coefficient for *Pessimist-Volume*×*D2011*, regardless of the volatility measures we use. The economic significance is also large. For example, when volatility is measured by *Garman-Klass* in Column 2, the volatility-volume relation of *Pessimistic-Volume* drops to -0.0057 (= -0.0135 + 0.0078) after December 5, 2011, a decline about 42% (= 0.0057/0.0135) of its original effect. This supports our hypothesis that the negative volatility-volume relation of the pessimistic investors weakens with less restricted short-sale rules. However, the interaction term of *Pessimist-Volume*×*D2013* does not have a significant coefficient. This can be attributed to the fact that additional 4% short-sale coverage in the CSI 300 Index after January 31, 2013 does not make significant difference comparing to the previous 96% short-sale coverage.

Again, there is no significant relation between the *Volatility* and *Optimist-Volume*, and the interaction terms of *Optimist-Volume*×*D2011* and *Optimist-Volume*×*D2013* do not have significant coefficients as well.

Overall, these results support our first two hypotheses that futures return volatility is more likely to be negatively correlated with the trading activity of large investors who cannot express their pessimistic views through short selling stocks, but can only hold net short positions in index futures. This negative volatility-volume relation of the pessimistic volume attenuates with the less restricted short-sale rules.

5.3 Robust Results of the Intraday 1-Minute Based Volatilities

In this subsection, we report the results of a set of robustness checks for those presented in Section 5.1-5.2.[19] First, we repeat the tests regarding equations (4) and (5) using Generalized Linear Models (GLM) estimations with the Newton-Raphson maximum likelihood optimization (based on Nelder and Wedderburn, 1972; McCullagh and Nelder, 1989). The results using GLM regressions are presented in the Panel B of both Table III and Table IV, which are virtually unchanged from those using OLS with Newey-West standard errors.[20]

Second, our pessimistic and optimistic volumes are constructed using the sum of volumes of the large traders to capture the aggregate information content of the pessimists versus optimists (in a similar spirit as those used in Chen and Diagler, 2000; Daigler and Wiley, 1999). However, our results could be biased by the actions of one or two large trading firms. To address this potential bias, we first drop the largest two traders in terms of trading volume on each trading day, and then reconstruct our pessimistic and optimistic volume variables in the same way as that discussed in Section 4.1. The regression results (untabulated) are almost identical to those using all traders. Furthermore, we repeat our tests using the median (instead of the sum) of the trading volume of pessimistic and optimistic investors, and again we find similar results.[21]

Lastly, we empirically verify the causality between trading volumes and volatilities using the pairwise Granger (1969) causality tests. The results in Table V show that Granger causality

[19] In addition to the robustness checks we describe in this section, using the Durbin-Watson statistics, we verify that our model specifications do not suffer from autocorrelation concerns.

[20] The GLM estimations allow different error distributions and correct for autocorrelation, so we do not need to include lagged volatilities. Nevertheless, including the lagged volatilities yield similar results as those without lagged volatilities.

[21] We do not tabulate the results to save space, and the results are available upon request.

runs one-way from the pessimistic volume to volatilities but not the other way (Panel A), and there is no Granger causality between the optimistic volume and volatilities (Panel B).

5.4 Conditional Volatility, Trading and Impact of Changes in Short-Sale Restrictions

In this subsection, we focus on the conditional volatility estimates. We model the volatility-volume relation in the CSI 300 Index futures using the GARCH-in-Mean (GARCH-M) representation of Engle et al. (1987). Return and conditional variance equations using GARCH-M (2,2) are given as:[22]

$$R_t = \lambda_0 + \lambda_1 \log(h_t) + \varepsilon_t \tag{6}$$

where conditional variance $h_t = \mathrm{var}(\varepsilon_t)$ is given by

$$\begin{aligned} h_t = \omega + \Sigma_{i=1}^{p}\alpha_i\varepsilon_{t-j}^2 + \Sigma_{j=1}^{q}\beta_j h_{t-j} + \Sigma_{k=1}^{2}\gamma_k \mathit{VolumeVariable}_{kt} \\ + \eta_1 \mathit{Small\text{-}Volume}_t + \eta_2 \mathit{Open\ Interest}_t + \eta_3 \Delta \mathit{Total\ Trading\ Volume}_t \end{aligned} \tag{7}$$

where $\mathit{VolumeVariable}_{kt}$ are $\mathit{Optimist\text{-}Volume}_t$ and $\mathit{Pessimist\text{-}Volume}_t$. The GARCH-M model is often used in financial applications where the expected return on an asset is related to the expected risk. The estimated coefficient on the expected risk is a measure of the risk-return tradeoff.[23]

Panel A of Table VI presents the results from equations (6) and (7). Again, our variable of interest is the *Pessimist-Volume*. We find that *Pessimist-Volume* is negatively correlated with the volatility at 5% significance level, but the *Optimist-Volume* does not have a significant relation with the volatility. Trading by small investors increases the volatility significantly at 10%

[22] Optimal lag lengths in this subsection are obtained using two information criterion: AIC and Schwarz-Bayesian information criterion (SBIC).

[23] We use the Student's *t*-distribution as the conditional distribution of the error terms and carry out our estimations with the Berndt-Hall-Hall-Hausman (BHHH) optimization algorithm.

significance level. This result is consistent with that presented in Table III and verifies our Hypothesis 1.

We re-estimate the time-varying model of volatility-volume relation by incorporating the effects of the changes in the number of stocks allowed for short selling in the spot market. We add two short-sale restrictions dummy variables, *D2011* and *D2013*, for the sample periods after December 5, 2011 and January 31, 2013, respectively. The conditional variance equation is given by:

$$\begin{aligned} h_t = {} & \omega + \Sigma_{i=1}^{p}\alpha_i\varepsilon_{t-j}^2 + \Sigma_{j=1}^{q}\beta_j h_{t-j} + \Sigma_{k=1}^{2}\gamma_k VolumeVariable_{kt} + \Sigma_{j=1}^{2}\phi_j Dummy_{jt} \\ & + \Sigma_{k=1}^{2}\Sigma_{j=1}^{2}\psi_{kj} VolumeVariable_{kt} \times Dummy_{jt} + \eta_1 Small\text{-}Volume_t \\ & + \eta_2 Open\ Interest_t + \eta_3 \Delta Total\ Trading\ Volume_t \end{aligned} \tag{8}$$

where $Dummy_{jt}$ variables are $D2011_t$ and $D2013_t$. The interaction terms of the volume variables and short-sale restrictions dummies are our main interest. Panel B of Table VI presents the results from equations (6) and (8). We show that *Pessimist-Volume*×*D2011* has a significant positive coefficient, which again supports our Hypothesis 2 that the negative volatility-volume relation of pessimistic investors gets weaker with less restricted the short-selling rules. The coefficient of *Pessimist-Volume*×*D2013* is not significant due to the smaller change in the short-sale rules on the CSI 300 Index in 2013.

We also apply the TGARCH and EGARCH representations to estimate the time-varying volatility. We use these asymmetric time-varying volatility estimates to incorporate the asymmetric responses to good and bad news. Results using asymmetric volatility estimates are expected to provide stronger support for our hypothesis if the negative volatility-volume relation still holds for pessimistic large investors after taking into account the different response of volatility to bad news, i.e., pessimistic views.

TARCH, or Threshold ARCH, and TGARCH were introduced independently by Zakoïan (1994) and Glosten et al. (1993). The generalized specification for the conditional variance is given by:

$$h_t = \omega + \Sigma_{i=1}^{p} \alpha_i \varepsilon_{t-j}^2 + \Sigma_{j=1}^{q} \beta_j h_{t-j} + \Sigma_{k=1}^{n} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- \qquad (9)$$

where $I_t^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise.

In this model, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$, have different effects on the conditional variance; good news has an impact of α_i, while bad news has an impact of $\alpha_I + \gamma_i$, if γ_i >0, bad news increases volatility comparing to good news, and this suggests that there is a leverage effect for the *i*-th order. If γ_i =0, the news impact is symmetric.

The EGARCH, or Exponential GARCH, model was proposed by Nelson (1991). The specification for the conditional variance is:

$$\log(h_t) = \omega + \Sigma_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}^{1/2}} \right| + \Sigma_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}^{1/2}} + \Sigma_{j=1}^{q} \beta_j \log(h_{t-j}) \qquad (10)$$

Note that the left-hand side is the *log* of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and the forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_i < 0$. The impact is symmetric if γ_i =0.

Panel A and Panel B of Table VII presents the TGARCH (1,1) and EGARCH (1,1) with ARCH in mean estimation of time-varying volatility, respectively. The significant positive (negative) coefficients on $\varepsilon_{t-1}^2 I_{t-1}^-$ ($\varepsilon_{t-1} / h_{t-1}^{1/2}$) in Panel A of TGARCH (Panel B of EGARCH) estimations confirm the asymmetric nature of conditional volatility.

Table VIII presents the estimation results of equation (5) with the time-varying volatility estimates we obtained from TGARCH and EGARCH models.[24] We document again that the *Pessimist-Volume* is negatively related to the volatility, and this relation becomes less negative with *D2011*. Furthermore, we find the coefficients of *Pessimist-Volume×D2013* are also positively significant at 10% (5%) level in TGARCH (EGARCH). The coefficients of the interaction terms of the short-sale restrictions dummies and the *Optimist-Volume* are not statistically significant.

Overall, these results obtained from the conditional volatility-volume relation are consistent with those found in Sections 5.1-5.3, and provide robust and stronger support for our hypothesis on the effects of spot market short-sale restrictions on the volatility-volume relation in the CSI 300 Index futures contracts. Our findings hold even after taking into account of the asymmetric responses to good versus bad news using TGARCH and EGARCH.

5.5 Trader Type, Sentiment and Index Futures Volatility

In this subsection, we focus on the volatility-volume relations of the top 20 largest traders based on their exchange membership: trading members versus clearing members. We examine the pessimistic and optimistic volume of the two member types and the volatility measures of *Absolute Return*, *Garman-Klass*, *Rogers-Satchell*, and *Parkinson* using the following regression:

$$\begin{aligned} Volatility_t = \alpha &+ \beta_1 Trading\ Member\ Pessimist\text{-}Volume_t + \beta_2 Clearing\ Member\ Pessimist\text{-}Volume_t \\ &+ \beta_3 Trading\ Member\ Optimist\text{-}Volume_t + \beta_4 Clearing\ Member\ Optimist\text{-}Volume_t \\ &+ \beta_5 Small\text{-}Volume_t + \beta_6 Volatility_{t-1} + \beta_7 Volatility_{t-2} + \beta_8 Open\ Interest_t \\ &+ \beta_9 \Delta Total\ Trading\ Volume_t + \varepsilon_t \end{aligned} \tag{11}$$

[24] Since we do not detect persistence in time-varying asymmetric volatility measures, the models in Table VIII do not include lagged volatilities.

where *Trading Member (Clearing Member) Pessimist-Volume* represent the trading volume by pessimistic exchange member types and *Trading Member (Clearing Member) Optimist-Volume* represent the trading volume by optimistic exchange member types, as defined in Section 4.1.

Table IX presents the estimation results of equation (11). The first pattern we observe is that the *Trading Member Pessimist-Volume* is negatively correlated with the futures return volatility under all volatility measures at the 1% or 5% significance level, while the *Clearing Member Pessimist-Volume* is insignificantly or positively related to the return volatility. These results suggest that the volume of trading members is more informative than that of the clearing members. Because clearing members trade for their own accounts as well as for their clients, the aggregated trading volumes represent various views and motivations and hence are less informative.

Furthermore, we find that neither the *Trading Member Optimist-Volume* nor the *Clearing Member Optimist-Volume* is significantly correlated with the futures return volatility, and the trading volume of small investors positively correlates with the futures return volatility. These findings demonstrate that the trading of pessimistic trading members is relative more informative than that of the optimistic trading members, as well as clearing members and small investors.

5.6 Index Futures Return and Sentiment, Investor Type Based Net-Demand

To provide more evidence on the information content of large pessimistic investors' activities, we investigate whether the net demands (positions) of large pessimistic investors can better prediction future returns. We partition the net demand into *Pessimist-Net-Demand* and

Optimist-Net-Demand, as described in Section 4.1, and we examine their futures return predictability using the following model:[25]

$$\begin{aligned} Return_{t+1} = \alpha &+ \beta_1 Pessimist\text{-}Net\text{-}Demand_t + \beta_2 Optimist\text{-}Net\text{-}Demand_t \\ &+ \beta_3 \Delta Total\ Trading\ Volume + \varepsilon_{t,t+1} \end{aligned} \tag{12}$$

where $Return_{t+1}$ represents the one-day-ahead returns of futures contracts. The empirical results for equation (12) are presented in Table X.

Column 1 shows that net demands of large investors with pessimistic views of the underlying spot market (*Pessimist-Net-Demand*) are positively related with the one-day-ahead returns of futures contracts, while those of the optimistic investors (*Optimist-Net-Demand*) are insignificantly correlated with the one-day-ahead returns. We find supporting evidence that net positions of large investors with pessimistic views of underlying stocks, better predict future returns than net positions of the optimistic investors.

In Column 2 of Table X, we consider whether the net demands of the large pessimistic trading members and clearing members predict future returns differently using the following expanded model:

$$\begin{aligned} Return_{t+1} = \alpha &+ \beta_1 Trading\ Member, Pessimist\text{-}Net\text{-}Demand_t + \beta_2 Clearing\ Member, Pessimist\text{-}Net\text{-}Demand_t \\ &+ \beta_3 Trading\ Member, Optimist\text{-}Net\text{-}Demand_t + \beta_4 Clearing\ Member, Optimist\text{-}Net\text{-}Demand_t \\ &+ \beta_5 \Delta Total\ Trading\ Volume + \varepsilon_{t,t+1} \end{aligned} \tag{13}$$

We document a significant positive relation between the one-day-ahead returns in futures markets and net demands of large pessimistic trading members (*Trading Member Pessimist-Net-Demand*). We do not find significant return predictability using the net demands of the optimistic trading members as well as both the pessimistic and optimistic clearing members.

[25] Because sum of the net demands of pessimistic and optimistic large investors and that of the small investors equals to zero, we do not include the net demands of small investors in equations (12) and (13). Additionally, open interest is not included because the net-demand variables are scaled by open interest.

Overall, the evidence that the net positions of the large pessimistic investors can predict one-day-ahead futures returns supports our Hypothesis 3 that with the spot market short-sale restrictions, trading activity of large pessimistic investors, especially that of the trading members, better predicts future returns than that of optimistic investors.

6. Conclusion

This paper analyzes the effects of spot market short-sale restrictions on the trading of derivatives contracts using detailed information on large traders' volume and positions. Specifically, we investigate the volatility-volume relation and return predictability in the stock index futures markets. Our contribution to the literature, in part, is based on both our use of the unique and transparent dataset, i.e., the daily disclosure of the trading volume and positions of largest 20 traders in the stock index futures market, and the unique natural experiment of the gradual removal of short-sale restrictions created by the short-sale pilot program in China.

Our paper explores, for the first time, the effects of spot market short-sale constraints on futures market, specifically on the trading of stock index futures contracts. Due to short-sale constraints, the pessimistic views of investors cannot be expressed in the spot market; in contrast, investors can express their optimistic views by holding long positions in both the spot and futures markets. Hence, we expect the futures trading of the pessimistic investors to be relatively more informative than that of the optimistic investors. We find supporting evidence that the negative volatility-volume relation is mostly associated with the trading volume of pessimistic investors, a group of investors holding negative net positions of futures contracts, and this negative volatility-volume relation attenuates with less restricted short-sale rules. Moreover, the net demand of the large pessimistic investors predicts returns in futures contracts, and this prediction is not significant in the case of optimistic investors. Our empirical findings survive a bunch of robustness checks, including four different intraday based and two asymmetric time-varying estimates of volatility, alternative volume measures, and different econometric specifications.

We extend the research by Battalio and Schultz (2011), Grundy et al. (2012), among others, which focus on the effects of 2008 short-sale ban on the equity option markets. Our study contributes the literature on equity market short-sale restrictions by presenting the initial evidence of their impact on stock index futures market using a set of particularities of the Chinese equity markets. Our study also shed light on the informational efficiency of short sales that policymakers should consider when contemplating intervening in the market by imposing restrictions. As the spot market short-sale restriction is lifted, the information advantage of the net short futures traders attenuates, a change indicating that the information of the pessimistic investors gradually gets incorporated into the underlying markets with less restricted short-sale rules. Therefore, policymakers/regulators should recognize that restricting short sales is detrimental to the overall efficiency of the markets, and that asset prices would better reflect the underlying values in the absence of short-sale restrictions.

References

Battalio, R. and Schultz P. (2011) Regulatory uncertainty and market liquidity: The 2008 short sale ban's impact on equity option markets, *Journal of Finance* **66**, 2013–2053.

Beber, A. and Pagano, M. (2013) Short-selling bans around the world: Evidence from the 2007-09 crisis, *Journal of Finance* **68**, 343–381.

Bessembinder, H. and Seguin, P. (1992). Futures-trading activity and stock price volatility, *Journal of Finance* **47**, 2015–2034.

Bessembinder, H. and Seguin, P. (1993) Price volatility, trading volume, and market depth: Evidence from futures markets, *Journal of Financial and Quantitative Analysis* **28**, 21–39.

Blau, B.M. and Wade, C. (2013) Comparing the information in short sales and put options, *Review of Quantitative Finance and Accounting* **41**, 567–583.

Boehmer, E., Jones, C. M., and Zhang, X. (2008) Which shorts are informed?, *Journal of Finance* **63**, 491–527.

Boehmer, E., Jones, C., and Zhang, X. (2013) Shackling short sellers: The 2008 shorting ban, *Review of Financial Studies* **26**, 1363–1400.

Boulton, T. and Braga-Alves, M. (2010) The skinny on the 2008 naked short-sale restrictions, *Journal of Financial Markets* **13**, 397–421.

Bris, A., Goetzmann, W. N., and Zhu N. (2007) Efficiency and the bear: Short sales and markets around the world, *Journal of Finance* **62**, 1029–1079.

Chan, K. and Fong, W. (2000) Trade size, order imbalance, and the volatility-volume relation, *Journal of Financial Economics* **57**, 247–273.

Chang, E.C., Cheng, J.W., and Yu, Y. (2007) Short-sales constraints and price discovery: Evidence from the Hong Kong market, *Journal of Finance* **62**, 2097–2121.

Chang, E.C., Luo, Y., and Ren, J. (2014) Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market, Journal of Banking and Finance 48, 411–424.

Chen, Z., and Daigler, R. (2008) An examination of the complementary volume-volatility information theories, *Journal of Futures Markets* **28**, 963–992.

Chen, J., Hong, H., and Stein, J. (2002) Breadth of ownership and stock returns, *Journal of Financial Economics* **66**, 171–205.

Clark, P. K. (1973) A subordinated stochastic process model with finite variances for speculative prices, *Econometrica* **41**, 135–155.

Daigler, R. and Wiley, M. (1999) The impact of trader type on the futures volatility-volume relation, *Journal of Finance* **54**, 2297–2316.

Diamond, D. and Verrecchia, R. (1987) Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* **18**, 277–311.

Dickey, D.A. and Fuller, W.A. (1979) Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association* **74**, 427–431.

Engle, R. F., Lilien, D. M. and Robins, R. P. (1987) Estimating Time Varying Risk Premia in the Term Structure: The ARCH-M Model, *Econometrica* **55**, 391–407.

Figlewski, S. (1981) Futures trading and volatility in the GNMA market, *Journal of Finance* **36**, 445–456.

Figlewski, S. and Webb, G. (1993) Options, short sales, and market completeness, *Journal of Finance* **48**, 761–777.

Forsberg, L. and Ghysels, E. (2007) Why do absolute returns predict volatility so well?, *Journal of Financial Econometrics* **5**, 31–67.

Garman, M. B. and Klass, M. J. (1980) On the estimation of security price volatilities from historical data, *Journal of Business* **53**, 67–78.

Granger, C. W. (1969) Investigating causal relations by econometric models and cross-spectral methods, *Econometrica* **37**, 424–438.

Grundy, B., Lim, B., and Verwijmeren, P. (2012) Do options markets undo restrictions on short sales? Evidence from the 2008 short-sale ban, *Journal of Financial Economics* **106**, 331–348.

Glosten, L. R., Jaganathan, R., and Runkle, D. (1993) On the relation between the expected value and the volatility of the normal excess return on stocks, *Journal of Finance* **48**, 1779–1801.

Harris, L. (1986) Cross-security tests of the mixture of distributions hypothesis, *Journal of Financial and Quantitative Analysis* **21**, 39–46.

Harris, M. and Raviv, A. (1993) Differences of option make a horse race, *Review of Financial Studies* **6**, 473–506.

Harrison, J. M. and Kreps, D. M. (1978) Speculative investor behavior in a stock market with heterogeneous expectations, *Quarterly Journal of Economics* **92**, 323–336.

Jarrow, R. (1980) Heterogeneous expectations, restrictions on short sales, and equilibrium asset prices, *Journal of Finance* **35**, 1105–1113.

Lamont, O. A. and Thaler. R. H. (2003) Can the market add and subtract? Mispricing in tech stock carve-outs, *Journal of Political Economy* **111**, 227–268.

McCullagh, P. and Nelder, J. A. (1989) Generalized Linear Models, Second ed. London, Chapman and Hall.

McMillan, D. G. and Philip, D. (2012) Short-sale constraints and efficiency of the spot-futures dynamics, *International Review of Financial Analysis* **24**, 129–136.

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

Nelder, J. A. and Wedderburn, R. W. M. (1972) Generalized linear models, *Journal of the Royal Statistical Society* **135**, 370–384.

Nelson, D. B. (1991) Conditional Heteroskedasticity in Asset Returns: A New Approach, *Econometrica* **59**, 347–370.

Newey, W. K. and West, K. D. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* **55**, 703–708.

Scheinkman, J. A. and Xiong, W. (2003) Overconfidence and speculative bubbles, *Journal of Political Economy* **111**, 1183–1219.

Shalen, C. T. (1993) Volume, volatility, and the dispersion of beliefs, *Review of Financial Studies* **6**, 405–434.

Stambaugh, R. F., Yu, J., and Yuan, Y. (2012) The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* **104**, 288–302.

Tauchen, G. E. and Pitts, M. (1983) The price variability-volume relationship on speculative markets, *Econometrica* **51**, 485–505.

Wang, C. (2002) The effect of net positions by type of trader on volatility in foreign currency futures markets, *Journal of Futures Markets* **22**, 427–450.

Wang, C. (2004) Futures trading activity and predictable foreign exchange market movements, *Journal of Banking and Finance* **28**, 1023–1041.

Wang, C. and Yu, M. (2004) Trading activity and price reversals in futures markets, *Journal of Banking and Finance* **28**, 1337–1361.

Xiong, W. and Yu, J. (2011) The Chinese warrant bubble, *American Economic Review* **101**, 2723–2753.

Zakoïan, J. M. (1994) Threshold heteroskedastic models, *Journal of Economic Dynamics and Control* **18**, 931–944.

Table I. Expansion of Pilot Program for Short-Selling: Changes in Spot Short-Sale Restrictions

Source: Bloomberg, China Financial Futures Exchange (CFFEX), Shanghai Stock Exchange, and Shenzhen Stock Exchange. The CSI 300 Stock Index components and index weights (based on market cap) for each day are obtained from Bloomberg. The number of stocks (and their identities) available for short-selling under the Short-Sale Pilot Program is obtained from corresponding exchange websites.

Changes in Short-Sale Restrictions	Date	Number of Shortable Stocks	Number of Shortable Stocks in CSI300 Index	Shortable Stocks' Market Cap. as % of CSI300 Index Market Cap.
Short-Sale Pilot Program Starts	3/31/2010	90	90	
CSI 300 Index Futures Trading Starts	4/16/2010	90	90	63.8%
Short-Sale Pilot Program Expansion-1	12/5/2011	278	260	96.0%
Short-Sale Pilot Program Expansion-2	1/31/2013	500	300	100%

Table II. Summary Statistics

Pessimist-Volume is defined the sum of trading volumes of the top 20 largest investors whose long futures position is smaller than their short position—investors with net short position at the end of previous trading day, *Optimist-Volume* is defined as the sum of trading volumes of the top 20 largest investors whose long futures position is greater than (or equal to) their short position—investors with net long position at the end of previous trading day, and *Small-Volume* is defined as is the trading volume by non-top 20 investors, which is calculated as the total futures trading volume minus the *Optimist-Volume* and the *Pessimist-Volume* on the same day. *Pessimist-Net-Demand* is the total long positions minus total short positions (scaled by daily total open interest) of large investors whose long positions in futures are less than their short positions; *Optimist-Net-Demand* is the total long positions minus total short positions (scaled by daily total open interest) of large investors whose long positions in futures are greater than (or equal to) their short positions. Volume and position variables are measured in the log of the number of contracts. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013.

Category	*Variable*	Mean	Median	Std.Dev	Min	Max
Futures Market	*Return (%)*	-0.044	-0.084	1.453	-7.115	6.476
	Trading Volume	12.651	12.620	0.634	10.640	14.050
	Open Interest	10.544	10.554	0.559	7.902	11.563
	Δ Total Trading Volume	0.0839	0.0390	0.3361	-0.7336	1.6356
Volatility Estimates	*Absolute Return (1min)*	0.051	0.047	0.016	0.020	0.140
	Garman-Klass (1min)	0.079	0.074	0.025	0.033	0.213
	Rogers-Satchell (1min)	0.038	0.035	0.013	0.014	0.113
	Parkinson (1min)	0.052	0.049	0.016	0.022	0.133
	TGARCH Variance	0.023	0.021	0.010	0.007	0.190
	EGARCH Variance	0.025	0.022	0.012	0.009	0.127
Volume by Pessimist, Optimist and Trader Type	*Small-Volume*	11.766	11.700	0.639	9.705	13.264
	Pessimist-Volume	11.505	11.441	0.688	9.181	13.180
	Optimist-Volume	11.258	11.260	0.682	8.695	12.837
	Trading Member, Pessimist-Volume	12.399	11.062	5.453	0.000	27.833
	Clearing Member, Pessimist-Volume	20.294	20.137	6.127	0.000	45.123
	Trading Member, Optimist-Volume	14.133	14.255	5.855	0.000	30.401
	Clearing Member, Optimist-Volume	21.913	21.655	6.826	4.716	40.106
Positions by Pessimist, Optimist and Trader Type	*Pessimist-Net-Demand*	-0.327	-0.317	0.086	-0.620	-0.098
	Optimist-Net-Demand	0.347	0.327	0.150	0.008	0.877
	Trading Member, Pessimist-Net-Demand	-0.086	-0.083	0.062	-0.298	0.101
	Clearing Member, Pessimist-Net-Demand	-0.188	-0.190	0.082	-0.417	0.073
	Trading Member, Optimist-Net-Demand	0.090	0.085	0.081	-0.181	0.394
	Clearing Member, Optimist-Net-Demand	0.203	0.187	0.124	-0.168	0.563

Table III. Trading Volume and Index Futures Volatility

Panel A. OLS Estimation

This table reports the estimation results for the equation (4). *Volatility*$_t$ takes on either *Absolute-Return*$_t$, *Garman-Klass*$_t$, *Rogers-Satchell*$_t$, or *Parkinson*$_t$ estimates. *Pessimist-Volume*$_t$ is defined as the total trading volume of investors whose long position in futures is smaller than their short position, i.e., trading firms with net short position at the end of previous trading day; and *Optimist-Volume*$_t$ is defined as the total trading volume of investors whose long position in futures is greater than (or equal to) their short position, i.e., trading firms with net short position at the end of previous trading day. *Small-Volume*$_t$ is defined as the total trading volume on day *t* minus the sum of *Pessimist-Volume*$_t$ and *Optimist-Volume*$_t$. *Volatility*$_{t-1}$ and *Volatility*$_{t-2}$ are 1- and 2-day lagged volatilities, *Open Interest*$_t$ is the daily total open interest, and *Δ Total Trading Volume*$_t$ is the change in the daily total trading volume. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. OLS estimations are applied and t-statistics (in parenthesis) are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors and covariance (Bartlett kernel) with optimal lag specification using AIC criterion. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	Daily Volatility based on intraday 1-minute intervals			
	Absolute Return	Garman-Klass	Rogers-Satchell	Parkinson
Pessimist-Volume$_t$	-0.0051***	-0.0094***	-0.0060***	-0.0058***
	(-4.44)	(-4.37)	(-4.23)	(-4.19)
Optimist-Volume$_t$	0.0014	0.0038	0.0024	0.0022
	(1.59)	(1.19)	(1.13)	(1.05)
Small-Volume$_t$	0.0041**	0.0074**	0.0047**	0.0053***
	(2.42)	(2.34)	(2.23)	(2.62)
Volatility$_{t-1}$	0.470***	0.566***	0.580***	0.549***
	(13.23)	(15.76)	(14.60)	(15.47)
Volatility$_{t-2}$	0.134***	0.0927***	0.0867***	0.0999***
	(4.01)	(3.24)	(2.90)	(3.35)
Open Interest$_t$	-0.0083***	-0.0166***	-0.0108***	-0.0106***
	(-9.37)	(-9.63)	(-9.36)	(-9.57)
ΔTotal Trading Volume$_t$	0.0123***	0.0238***	0.0148***	0.0155***
	(10.99)	(10.63)	(10.18)	(10.78)
Constant	-0.0207***	-0.0377***	-0.0220***	-0.0255***
	(-3.14)	(-3.11)	(-2.78)	(-3.25)
Number of Observations	864	864	864	864
Adjusted R^2	0.682	0.669	0.668	0.656

Table III–*Continued*

Panel B. Generalized Linear Models Estimation

This table reports the estimation results for the equation (4). All variables are defined similarly as those in Panel A. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. The GLM estimations (based on Nelder and Wedderburn 1972; McCullagh and Nelder 1989) are applied by fitting generalized linear models with Newton-Raphson maximum likelihood optimization. GLM estimation parameters: Family: Normal, Link: Identity, Dispersion computed using Pearson Chi-Square Coefficient covariance computed using the Newey-West HAC method with observed Hessian. Standard errors and covariance structure (Bartlett kernel) are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) methodology with optimal lag specification using AIC criterion. Z-statistics are reported in parenthesis. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	Daily Volatility based on intraday 1-minute intervals			
	Absolute Return	Garman-Klass	Rogers-Satchell	Parkinson
Pessimist-Volume$_t$	-0.0064***	-0.0127***	-0.0084***	-0.0079***
	(-4.06)	(-3.79)	(-3.72)	(-3.65)
Optimist-Volume$_t$	0.0009	0.0036	0.0025	0.0021
	(0.66)	(1.13)	(1.20)	(1.05)
Small-Volume$_t$	0.0108***	0.0209***	0.0130***	0.0139***
	(4.08)	(3.50)	(3.29)	(3.68)
Open Interest$_t$	-0.0145***	-0.0319***	-0.0212***	-0.0202***
	(-8.94)	(-8.41)	(-8.41)	(-8.38)
ΔTotal Trading Volume$_t$	0.0075***	0.0106***	0.0057***	0.0072***
	(7.34)	(5.73)	(4.90)	(6.05)
Constant	-0.0217	-0.0184	-0.00224	-0.0150
	(-1.58)	(-0.59)	(-0.11)	(-0.76)
Number of Observations	865	865	865	865
AIC	-6.5002	-5.1202	-5.9588	-6.0033
Log Likelihood	2817.33	2220.48	2583.19	2602.43
Chi^2 (LL Statistics)	714.52	710.83	670.31	712.87
Prob.(Chi^2)	0.0000	0.0000	0.0000	0.0000

Table IV. Impact of Changes in Spot Short-Sale Restrictions on the Volatility-Volume Relation

Panel A. OLS Estimation

This table reports the estimation results for the equation (5). In addition to the variable definitions provided in Table III, $Dummy_t$ (time serial dummy variables accounting for the changes in the short-sale restrictions) takes on $D2011_t$ which is 1 if trading day is on or after December 5, 2011, zero otherwise; and $D2013_t$ which is 1 if trading day is on or after January 31, 2013, zero otherwise. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. OLS estimations are applied and t-statistics (in parenthesis) are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors and covariance (Bartlett kernel) with optimal lag specification using AIC criterion. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	Daily Volatility based on intraday 1-minute intervals			
	Absolute Return	Garman-Klass	Rogers-Satchell	Parkinson
Pessimist-Volume$_t$	-0.0067***	-0.0135***	-0.0088***	-0.0085***
	(-4.83)	(-5.20)	(-4.99)	(-5.02)
Optimist-Volume$_t$	0.00170	0.0044	0.0031	0.0026
	(1.37)	(1.14)	(1.16)	(1.04)
D2011$_t$	0.0391**	0.0978***	0.0722***	0.0627***
	(2.38)	(3.39)	(3.84)	(3.37)
D2013$_t$	-0.0457	-0.0819	-0.0538	-0.0551
	(-1.24)	(-1.31)	(-1.34)	(-1.36)
*Pessimist-Volume * D2011$_t$*	0.0033**	0.0078***	0.0052***	0.0051***
	(2.28)	(2.83)	(2.81)	(2.92)
*Optimist-Volume * D2011$_t$*	0.0006	0.0018	0.0019	0.0010
	(0.41)	(0.65)	(1.18)	(0.51)
*Pessimist-Volume * D2013$_t$*	0.0030	0.0051	0.0030	0.0033
	(1.07)	(1.03)	(0.95)	(1.12)
*Optimist-Volume * D2013$_t$*	0.0008	0.0015	0.0013	0.0008
	(0.37)	(0.48)	(0.68)	(0.39)
Small-Volume$_t$	0.0046***	0.0096***	0.0065***	0.0067***
	(2.94)	(3.44)	(3.44)	(3.63)
Volatility$_{t-1}$	0.4730***	0.5740***	0.5850***	0.5580***
	(13.47)	(15.64)	(15.35)	(15.79)
Volatility$_{t-2}$	0.1300***	0.0934***	0.0882**	0.1010***
	(3.94)	(2.83)	(2.24)	(2.92)
Open Interest$_t$	-0.0049***	-0.0085***	-0.0052***	-0.0054***
	(-4.37)	(-3.75)	(-3.31)	(-3.76)
ΔTotal Trading Volume$_t$	0.0130***	0.0254***	0.0159***	0.0165***
	(11.60)	(11.67)	(11.30)	(11.77)
Constant	-0.0815***	-0.1950***	-0.1350***	-0.1260***
	(-5.14)	(-7.67)	(-8.07)	(-7.63)
Number of Observations	864	864	864	864
Adjusted R^2	0.698	0.687	0.688	0.674

Table IV–*Continued*

Panel B. Generalized Linear Models Estimation

This table reports the estimation results for the equation (5). All variables are defined similarly as those in Panel A. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. The GLM estimations (based on Nelder and Wedderburn 1972; McCullagh and Nelder 1989) are applied by fitting generalized linear models with Newton-Raphson maximum likelihood optimization. GLM estimation parameters: Family: Normal, Link: Identity, Dispersion computed using Pearson Chi-Square Coefficient covariance computed using the Newey-West HAC method with observed Hessian. Standard errors are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) methodology with optimal lag specification using AIC criterion. Z-statistics are reported in parenthesis. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	Daily Volatility based on intraday 1-minute intervals			
	Absolute Return	Garman-Klass	Rogers-Satchell	Parkinson
Pessimist-Volume$_t$	-0.0082***	-0.0179***	-0.0120***	-0.0111***
	(-4.56)	(-4.84)	(-4.80)	(-4.67)
Optimist-Volume$_t$	0.0030	0.0077	0.0052	0.0046
	(1.57)	(1.35)	(1.46)	(0.97)
D2011$_t$	0.0841***	0.2010***	0.1401***	0.1230***
	(2.95)	(3.45)	(3.47)	(3.32)
D2013$_t$	-0.0708	-0.1330	-0.0849	-0.0833
	(-1.35)	(-1.36)	(-1.30)	(-1.33)
*Pessimist-Volume * D2011$_t$*	0.0052***	0.0132***	0.0090***	0.0082***
	(2.54)	(3.06)	(3.13)	(2.97)
*Optimist-Volume * D2011$_t$*	0.0028	0.0056	0.0041	0.0033
	(1.37)	(1.27)	(1.33)	(1.18)
*Pessimist-Volume * D2013$_t$*	0.0049	0.0095	0.0057	0.0060
	(1.13)	(1.16)	(1.02)	(1.16)
*Optimist-Volume * D2013$_t$*	0.0015	0.0024	0.0018	0.0014
	(0.62)	(0.52)	(0.63)	(0.48)
Small-Volume$_t$	0.00948***	0.0195***	0.0126***	0.0129***
	(4.11)	(4.01)	(3.75)	(4.19)
Open Interest$_t$	-0.0110***	-0.0243***	-0.0158***	-0.0155***
	(-6.43)	(-6.70)	(-6.11)	(-6.62)
ΔTotal Trading Volume$_t$	0.0082***	0.0122***	0.0068***	0.0082***
	(8.12)	(6.65)	(6.17)	(6.97)
Constant	-0.0834***	-0.1772***	-0.1201***	-0.1120***
	(-3.07)	(-3.09)	(-3.02)	(-3.09)
Number of Observations	865	865	865	865
AIC	-6.5539	-5.1765	-6.0197	-6.0559
Log Likelihood	2846.59	2250.82	2615.52	2631.17
Chi^2 (LL Statistics)	818.94	819.14	783.51	815.14
Prob.(Chi^2)	0.0000	0.0000	0.0000	0.0000

Table V. Pairwise Granger Causality Tests

Panel A. Pessimistic Volume and Volatility

Null Hypothesis	F-Statistic	Prob.
Pessimist-Volume does not Granger Cause Absolute Return	1.9581	0.0252
Absolute Return does not Granger Cause Pessimist-Volume	0.1253	0.7234
Pessimist-Volume does not Granger Cause Garman-Klass	7.5769	0.0060
Garman-Class does not Granger Cause Pessimist-Volume	0.7831	0.3765
Pessimist-Volume does not Granger Cause Rogers-Satchell	9.4405	0.0022
Rogers-Satchell does not Granger Cause Pessimist-Volume	1.4346	0.2313
Pessimist-Volume does not Granger Cause Parkinson	7.2153	0.0074
Parkinson does not Granger Cause Pessimist-Volume	0.4789	0.4891
Pessimist-Volume does not Granger Cause E-GARCH	41.4155	0.0000
E-GARCH does not Granger Cause Pessimist-Volume	2.1733	0.1408
Pessimist-Volume does not Granger Cause T-GARCH	46.5893	0.0000
T-GARCH does not Granger Cause Pessimist-Volume	1.9705	0.1608

Panel B. Optimistic Volume and Volatility

Null Hypothesis	F-Statistic	Prob.
Optimist-Volume does not Granger Cause Absolute Return	0.0775	78.1%
Absolute Return does not Granger Cause Optimist-Volume	0.1723	67.8%
Optimist-Volume does not Granger Cause Garman-Klass	1.3786	24.1%
Garman-Class does not Granger Cause Optimist-Volume	1.5853	20.8%
Optimist-Volume does not Granger Cause Rogers-Satchell	2.4875	11.5%
Rogers-Satchell does not Granger Cause Optimist-Volume	2.3953	12.2%
Optimist-Volume does not Granger Cause Parkinson	0.9079	34.1%
Parkinson does not Granger Cause Optimist-Volume	1.3928	23.8%
Optimist-Volume does not Granger Cause E-GARCH	1.50492	11.7%
E-GARCH does not Granger Cause Optimist-Volume	1.81477	10.7%
Optimist-Volume does not Granger Cause T-GARCH	1.57732	16.4%
T-GARCH does not Granger Cause Optimist-Volume	2.0096	15.7%

Table VI. Time-varying Conditional Volatility Framework

Panel A. Trading and Time-varying Conditional Volatility of the CSI 300 Index futures

This panel reports the estimation results for the Equations (6) and (7) $R_t = \lambda_0 + \lambda_1 \log(h_t) + \varepsilon_t$, where conditional variance $h_t = \mathrm{var}(\varepsilon_t)$ is given by $h_t = \omega + \Sigma_{i=1}^{p}\alpha_i \varepsilon_{t-j}^2 + \Sigma_{j=1}^{q}\beta_j h_{t-j} + \Sigma_{k=1}^{2}\gamma_k \mathit{VolumeVariable}_{kt} + \eta_1 \mathit{Small\text{-}Volume}_t + \eta_2 \mathit{Open\ Interest}_t + \eta_3 \Delta \mathit{Total\ Trading\ Volume}_t$ where $\mathit{VolumeVariable}_{kt}$ are $\mathit{Optimist\text{-}Volume}_t$ and $\mathit{Pessimist\text{-}Volume}_t$.

Mean Equation

Variable	Constant	*log*(h_t)
Coefficient	0.01546	0.00175
z-Statistic	(3.134)***	(3.253)***

Conditional Variance Equation

Variable	Constant	ε^2_{t-1}	ε^2_{t-2}	h_{t-1}	h_{t-2}	*Pessimist Volume*$_t$	*Optimist Volume*$_t$	*Small Volume*$_t$	*Open Interest*$_t$	*ΔTrading Volume*$_t$	DoF Student's t-distribution
Coefficient	0.00025	0.04485	-0.04088	0.66805	-0.28716	-0.00003250	0.00000036	0.00003950	-0.00009410	0.00015200	7.00
z-Statistic	(3.807)***	(2.258)**	(-2.56)**	(6.598)***	(-3.878)***	(-2.225)**	(0.034)	(1.957)*	(-6.859)***	(8.295)***	(4.684)***
Adjusted R^2	0.00357	*Log likelihood*	2,777.6	*Durbin-Watson*	2.0072						

Panel B. Impact of Changes in Spot Short-Sale Restrictions on Time-varying Conditional Volatility-Volume Relation

This panel reports the estimation results for the Equations (6) and (8): $R_t = \lambda_0 + \lambda_1 \log(h_t) + \varepsilon_t$, where conditional variance $h_t = \mathrm{var}(\varepsilon_t)$ is given by

$$h_t = \omega + \Sigma_{i=1}^{p}\alpha_i \varepsilon_{t-j}^2 + \Sigma_{j=1}^{q}\beta_j h_{t-j} + \Sigma_{k=1}^{2}\gamma_k \mathit{VolumeVariable}_{kt} + \Sigma_{d=1}^{2}\phi_d \mathit{Dummy}_{dt} + \Sigma_{k=1}^{2}\Sigma_{d=1}^{2}\psi_{kd}\mathit{VolumeVariable}_{kt} \times \mathit{Dummy}_{dt} + \eta_1 \mathit{Small\text{-}Volume}_t + \eta_2 \mathit{Open\ Interest}_t + \eta_3 \Delta \mathit{Total\ Trading\ Volume}_t$$

where $\mathit{VolumeVariable}_{kt}$ are $\mathit{Optimist\text{-}Volume}_t$ and $\mathit{Pessimist\text{-}Volume}_t$; Dummy_{jt} variables are $\mathit{D2011}_t$ and $\mathit{D2013}_t$.. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

Mean Equation

Variable	Constant	*log*(h_t)
Coefficient	0.02916	0.00341
z-Statistic	(4.078)***	(4.112)***

Conditional Variance Equation

Variable	Constant	ε^2_{t-1}	h_{t-1}	*Pessimist Volume*$_t$	*Optimist Volume*$_t$	*Small Volume*$_t$	*Open Interest*$_t$	*ΔTrading Volume*$_t$	*Pessimist Vol*D2011*$_t$	*Pessimist Vol*D2013*$_t$	*Optimist Vol*D2011*$_t$	*Optimist Vol*D2013*$_t$	DoF Student's t-distribution
Coefficient	0.00101	0.00698	-0.18282	-0.0000358	0.0000232	0.0000700	-0.00028	0.0000546	0.0000069	0.0000076	0.0000080	-0.0000076	3.43
z-Statistic	(3.827)***	(2.359)*	(-1.208)	(-5.438)***	(0.619)	(1.973)**	(-7.14)***	(2.835)***	(1.888)**	(2.564)**	(0.213)	(-0.245)	(6.517)***
Adjusted R^2	0.00567	*Log likelihood*	2,762.6	*Durbin-Watson*	2.0097								

Table VII. Estimation of Asymmetric Time-varying Volatility

Panel A. TGARCH-M(1,1) Model Estimation

This panel reports the estimation results for the Equations (6) and (9): $R_t = \lambda_0 + \lambda_1 \log(h_t) + \varepsilon_t$, where conditional variance is given $h_t = \mathrm{var}(\varepsilon_t)$ by $h_t = \omega + \Sigma_{i=1}^{p}\alpha_i \varepsilon_{t-j}^2 + \Sigma_{j=1}^{q}\beta_j h_{t-j} + \Sigma_{k=1}^{n}\gamma_k \varepsilon_{t-k}^2 I_{t-k}^-$ where $I_t^- = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In this model, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$ have differential effects on the conditional variance.

			Mean Equation				
			Variable	Constant	*log*(h_t)		
			Coefficient	0.03234	0.00392		
			z-Statistic	(2.344)**	(2.42)**		
			Conditional Variance Equation				
Variable	Constant	ε^2_{t-1}	$\varepsilon^2_{t-1}*I^-_{t-1}$	h_{t-1}	*Open Interest$_t$*	*ΔTrading Volume$_t$*	DoF Student's t-distribution
Coefficient	0.00023	-0.01567	0.05605	0.48539	-0.000091	0.000067	3.80
z-Statistic	(3.106)***	(-5.663)***	(2.267)***	(3.84)***	(-6.891)***	(3.976)***	(6.039)***
Adjusted R^2	0.00262	*Log likelihood*	2,745.0	*Durbin-Watson*	1.9951		

Panel B. EGARCH-M(1,1) Model Estimation

This panel reports the estimation results for the Equations (6) and (10): $R_t = \lambda_0 + \lambda_1 \log(h_t) + \varepsilon_t$, where conditional variance $h_t = \mathrm{var}(\varepsilon_t)$ is given by $\log(h_t) = \omega + \Sigma_{i=1}^{p}\alpha_i \left|\frac{\varepsilon_{t-i}}{h_{t-i}^{1/2}}\right| + \Sigma_{k=1}^{r}\gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}^{1/2}} + \Sigma_{j=1}^{q}\beta_j \log(h_{t-j})$ where $\varepsilon_{t-i} > 0$ is good news and $\varepsilon_{t-i} < 0$ is bad news. Both asymmetric GARCH models are estimated using log variance as the ARCH in mean parameter, Student's t representing the distribution of the errors (with optimal degrees of freedom) based on the BHHH optimization method. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

			Mean Equation				
			Variable	Constant	*log*(h_t)		
			Coefficient	0.00331	0.00050		
			z-Statistic	(3.566)***	(4.618)***		
			Conditional Variance Equation				
Variable	Constant	$\lvert \varepsilon_{t-1}/h^{1/2}_{t-1} \rvert$	$\varepsilon_{t-1}/h^{1/2}_{t-1}$	*log*(h_{t-1})	*Open Interest$_t$*	*ΔTrading Volume$_t$*	DoF Student's t-distribution
Coefficient	-6.64889	-0.00633	-0.06416	-0.87656	-1.33338	0.39519	3.62
z-Statistic	(-3.654)***	(-2.558)**	(-3.509)***	(-14.973)***	(-6.875)***	(2.996)***	(6.159)***
Adjusted R^2	0.00197	*Log likelihood*	2,745.4	*Durbin-Watson*	2.0087		

Table VIII. Impact of Changes in Spot Short-Sale Restrictions on the Asymmetric Time-varying Volatility-Volume Relation

This table reports the estimation results for the equation (5). *Volatility*$_t$ takes on either TGARCH or EGARCH, volatility estimates we obtained from asymmetric GARCH models. Again, *Pessimist-Volume*$_t$ is defined as the total trading volume of investors whose long position in futures is smaller than their short position, i.e., trading firms with net short position at the end of previous trading day; and *Optimist-Volume*$_t$ is defined as the total trading volume of investors whose long position in futures is greater than (or equal to) their short position, i.e., trading firms with net short position at the end of previous trading day., *Dummy*$_t$ (time serial dummy variables accounting for the changes in the short-sale restrictions) takes on *D2011*$_t$ which is 1 if trading day is on or after December 5, 2011, zero otherwise; and *D2013*$_t$ which is 1 if trading day is on or after January 31, 2013, zero otherwise. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. OLS estimations are applied and t-statistics (in parenthesis) are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors and covariance (Bartlett kernel) with optimal lag specification using AIC criterion. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	Time-varying Asymmetric Volatility Estimates	
	TGARCH Volatility	EGARCH Volatility
Pessimist-Volume$_t$	-0.0018*	-0.0025**
	(-1.81)	(-2.19)
Optimist-Volume$_t$	0.0029	0.00274
	(1.43)	(1.56)
D2011$_t$	-0.0391***	-0.0408***
	(-2.59)	(-2.73)
D2013$_t$	-0.0361**	-0.0224**
	(-2.24)	(-2.19)
*Pessimist-Volume * D2011*$_t$	0.0006***	0.0023***
	(2.80)	(2.97)
*Optimist-Volume * D2011*$_t$	0.0046	0.0015
	(1.31)	(1.10)
*Pessimist-Volume * D2013*$_t$	0.0008*	0.0001**
	(1.87)	(2.41)
*Optimist-Volume * D2013*$_t$	-0.0020	0.0006
	(-1.57)	(0.65)
Small-Volume$_t$	0.0026***	0.0039***
	(2.61)	(3.18)
Open Interest$_t$	-0.0246***	-0.0236***
	(-5.19)	(-14.19)
ΔTotal Trading Volume$_t$	0.0081***	0.0074***
	(10.32)	(11.15)
Constant	0.1560***	0.1930***
	(2.51)	(9.26)
Number of Observations	865	865
Adjusted R^2	0.6841	0.6895

Table IX. Trader Type and Index Futures Volatility

This table reports the estimation results for the equation (11). *Trading Member* (*Clearing Member*) *Pessimist-Volume* represent the trading volume by pessimist exchange member types and *Trading Member* (*Clearing Member*) *Optimist-Volume* represent the trading volume by optimist exchange member types, as defined in Section 4.1. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. OLS estimations are applied and t-statistics (in parenthesis) are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors and covariance (Bartlett kernel) with optimal lag specification using AIC criterion. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	Daily Volatility based on intraday 1-minute intervals			
	Absolute Return	Garman-Klass	Rogers-Satchell	Parkinson
Trading Member, Pessimist-Volume$_t$	-0.000428***	-0.000222***	-0.000152**	-0.000116***
	(-2.76)	(-3.23)	(-2.33)	(-2.79)
Clearing Member, Pessimist-Volume$_t$	0.000477	0.000122**	0.000818**	0.000583*
	(0.63)	(2.42)	(2.13)	(1.86)
Trading Member, Optimist-Volume$_t$	-0.000014	0.000375	0.000025	0.000023
	(-0.57)	(0.79)	(0.78)	(0.59)
Clearing Member, Optimist-Volume$_t$	0.000045	0.000157	0.000102	0.000756
	(0.71)	(1.24)	(1.22)	(0.93)
Volatility$_{t-1}$	0.4781***	0.5780***	0.5934***	0.5596***
	(13.58)	(15.68)	(15.50)	(15.21)
Volatility$_{t-2}$	0.1350***	0.0940***	0.0872***	0.1010***
	(4.44)	(3.03)	(2.68)	(3.26)
Small-Volume$_t$	0.0097***	0.0188***	0.0120***	0.0124***
	(11.50)	(11.89)	(11.28)	(12.12)
Open Interest$_t$	-0.0075***	-0.0153***	-0.0100***	-0.0099***
	(-8.59)	(-8.91)	(-8.52)	(-9.12)
ΔTotal Trading Volume$_t$	0.0124***	0.0243***	0.0151***	0.0157***
	(11.44)	(11.20)	(10.87)	(11.23)
Constant	-0.0261***	-0.0497***	-0.0297***	-0.0327***
	(-4.33)	(-4.50)	(-4.03)	(-4.62)
Number of Observations	864	864	864	864
Adjusted R^2	0.677	0.733	0.728	0.723

Table X. Futures Returns Prediction of Trader Type based Net-Demands

This table reports the estimation results for the equation (12) and for the equation (13). $Return_{t+1}$ represents the one-day-ahead returns of futures contracts, *Pessimist-Net-Demand* is the total long positions minus total short positions (scaled by daily total open interest) of large investors whose long positions in futures are less than their short positions, scaled by the total open interest at the end of each trading day; *Optimist-Net-Demand* is the total long positions minus total short positions (scaled by daily total open interest) of large investors whose long positions in futures are greater than (or equal to) their short positions, scaled by the total open interest at the end of each trading day. Our sample of the CSI 300 Index futures contracts is from April 16, 2010 to November 15, 2013. OLS estimations are applied and t-statistics (in parenthesis) are calculated from heteroscedasticity and autocorrelation consistent (HAC) Newey-West (1987) standard errors and covariance (Bartlett kernel) with optimal lag specification using AIC criterion. *, **, and *** denote statistical significance (two tailed) at the 10%, 5%, and 1% levels, respectively.

	$Return_{t+1}$	$Return_{t+1}$
$Pessimist\text{-}Net\text{-}Demand_t$	0.8680**	
	(1.99)	
$Optimist\text{-}Net\text{-}Demand_t$	0.6820	
	(0.91)	
Trading Member, $Pessimist\text{-}Net\text{-}Demand_t$		1.4770***
		(2.69)
Clearing Member, $Pessimist\text{-}Net\text{-}Demand_t$		-0.3270
		(-0.45)
Trading Member, $Optimist\text{-}Net\text{-}Demand_t$		1.0460
		(1.17)
Clearing Member, $Optimist\text{-}Net\text{-}Demand_t$		1.0510
		(1.09)
$\Delta Total\ Trading\ Volume_t$	0.2930***	0.3180***
	(2.73)	(3.07)
Constant	-3.840***	-4.060***
	(-2.60)	(-2.86)
Number of Observations	865	865
Adjusted R^2	0.015	0.02

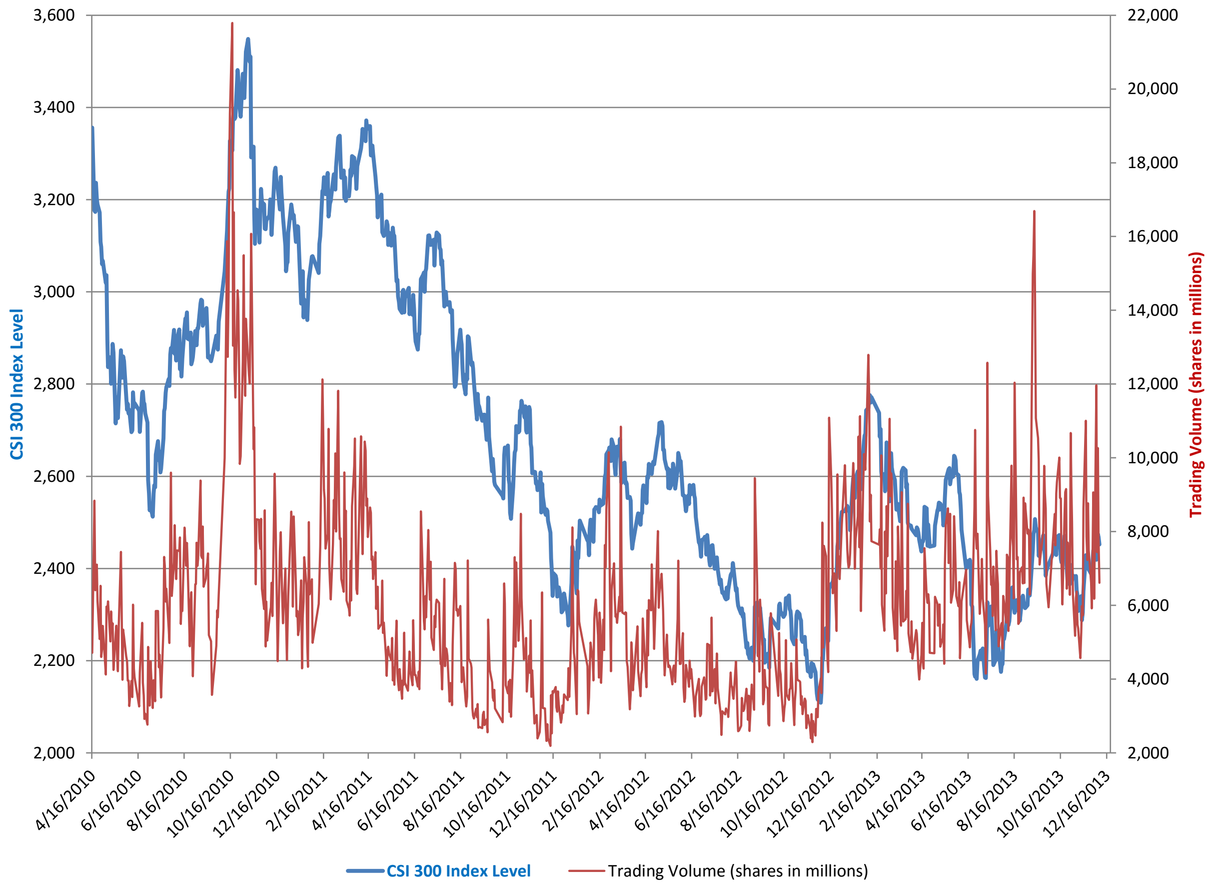

Figure 1. CSI 300 Stock Index Level and Spot Trading Volume. Source: Bloomberg. Our sample is from April 16, 2010 to November 15, 2013.