The Impact of the CSI300 stock index futures: positive feedback trading and autocorrelation of stock returns

Abstract

This study examines the impact of the introduction of the China Security Index (CSI) 300 stock index futures on the underlying stock market based on a feedback trading model. We focus on examining the interaction between time-varying autocorrelation and conditional volatility in the returns of both spot index and index futures markets. An extended exponential AR (EAR)-GJR-GARCH model is employed for the analysis by using high-frequency data. Our research reveals a few interesting findings. The introduction of the CSI 300 stock index futures plays a significant role in reducing the volatility of the underlying CSI 300 stock index market; it intensifies positive feedback trading in the underlying stock market and thus reduces the informational efficiency in the stock index market. Moreover, the CSI 300 stock index futures market attracts positive feedback trading itself, which may destabilise asset prices of the underlying spot index through the index arbitrage. We also find that trading volume is inversely related to autocorrelation of intraday returns and positive feedback trading is more intense in the event of a market downturn than a market upturn in both the spot and futures markets.

Key words: feedback trading, EAR-GJR-GARCH model, CSI 300 stock index, CSI 300 stock index futures, time-varying autocorrelation, conditional volatility

JEL Code: G14, G15

1. INTRODUCTION

It has been well established by now that stock index returns are autocorrelated at high frequencies (e.g. Cutler, Poterba and Summers, 1991; Koutmos, 1997a). On the one hand, stock index returns may be positively autocorrelated. Microstructure biases caused by non-synchronous trading or time-varying short-term expected risk premia is cited in the literature to explain this phenomenon (e.g. Scholes and Williams, 1977; Fama and French, 1988; Conrad and Kaul, 1988). Non-synchronous trading can cause autocorrelation in index returns because the component stocks in index portfolio do not trade in every instant (Koutmos, 1997a). In contrast, autocorrelation induced by changes in expected risk premia implies predictability of returns. However, such predictability is compatible with the EMH (efficient market hypothesis), as has been discussed in the literature in the context of modern intertemporal asset pricing models of the type of Lucas (1978) and Breeden (1979).

On the other hand, autocorrelation in stock index returns could be negative. In the case of transaction data, it has been shown that the bid-ask bounce can induce first-lag negative autocorrelation (Roll, 1984; Chen, Su and Huang, 2008). Transaction price bounces randomly between bid and ask prices. It is possible that a large number of stocks may close at either the bid or ask at the same time in exceptional periods (Sentana and Wadhwani, 1992). Nonetheless, regardless of whether autocorrelation in stock index returns behaves positively or negatively in these studies, autocorrelation is constant and not evolved over time.

Recently, it has been argued in the literature that autocorrelation in stock index returns can change over time. One of the most popular explanations on time-varying autocorrelation is the feedback trading model. Under this model, there are two heterogeneous groups of investors assumed in the stock market. One group is recognised as informed traders who make investment decisions based on maximising expected utility. The other group is feedback traders who buy and sell shares based on past trends of stock prices. The best known feedback trading strategy is positive feedback trading, in which one buys when prices move up and sells when prices move down. Positive feedback trading strategy is in accordance with extrapolative expectations, technical analysis, stop-loss orders and portfolio insurance (Antoniou, Koutmos and Pescetto, 2011). Positive feedback traders are believed to be noise traders who destabilise the market (Antoniou, Koutmos and Pericli, 2005). In the presence of positive feedback trading, prices are pulled away from fundamental values. Paradoxically, risk-averse arbitragers cannot exploit such deviations because the risk is high. On the contrary, they demand more shares in anticipation of the response of positive feedback traders, which pushes stock prices further away from their fundamental values. Thus, the interaction of positive feedback traders and rational speculators destabilises the stock market in the short-run. Eventually, rational speculators liquidate their position and prices move back to their fundamental values (De Long, Shleifer, Summers and Waldman, 1990b; Antoniou, Koutmos and Pescetto, 2011). The presence of positive feedback trading induces autocorrelation in stock returns to be negatively related with the level of volatility. Evidence has been provided by Sentana and Wadhwani (1992), Koutmos (1997a &b), McKenzie and Faff (2003), Antoniou et al. (2005), among others.

Another strand of research is on investigating whether the introduction of futures trading stabilises or destabilises the underlying spot markets. To date, existing theoretical models do not yield a clear conclusion on how trading in the futures markets impacts spot markets. One argument is in favour of derivatives markets, in the sense that they increase market liquidity by attracting more investors to the spot markets and higher liquidity results in lower volatility in the spot markets (Antoniou et al., 2011). Another argument is suggested by Cox (1976) and Ross (1989), which proposes that index futures trading increases the volatility of the underlying spot markets as it increases the flow of information for spot markets. Higher volatility resulting from higher informational efficiency would be considered as a positive development in the financial markets (Antoniou et al., 2011). However, information efficiency cannot be warranted in the spot markets if the information coming from the futures markets is mostly ‘noise’. Since index futures market has a feature of attracting noise traders, particularly positive feedback traders, this will increase the volatility in the futures market. Subsequently, the impact is transmitted to the spot markets through the process of arbitrage. Hence, in such case, the potential for destabilisation would be real. In light of the above, whether the futures trading can stabilise or destabilise the spot markets depends on which type of investors dominate the market (Antoniou et al., 2005). Thus, it is purely an empirical question whether futures trading stabilise the spot markets or not in the literature.

The China Securities Index (CSI) 300 stock index, which is also called HuShen (HS) 300 stock index, was jointly launched by the Shanghai Stock Exchange and the Shenzhen Stock Exchange on April 8th, 2005. It comprises of 300 stocks which are most heavily traded in the Chinese A-share markets[1] and represents approximately 70% of total market capitalisation of both Shanghai and Shenzhen stock exchanges. The CSI 300 stock index aims to reflect the price fluctuation and performance of the Chinese A-share markets. It is designed for performance benchmark and as base for derivatives innovation, etc. Now, the CSI 300 index is widely accepted as an overall reflection of the general movements and trends of the Chinese A-share markets (Yang, Yang and Zhou, 2012).

To further develop Chinese stock markets and provide domestic investors with a tool to hedge risks in the stock markets, the CSI300 index futures contract was launched on April

[1] The Chinese A-share markets are only available for Chinese domestic investors. However, the Chinese B-share markets are available for both domestic and foreign investors.

16th, 2010 on the China Financial Futures Exchange (CFFEX). The trading of the stock index futures contracts in China ends the era in which domestic traders are constrained to short-sell stocks in the market. Meanwhile, it opens a new era of confrontation between the long and short sides of Chinese stock markets (Yang et al., 2012). Thus it is important to know how this event affects the Chinese stock markets.

This study aims to examine how the introduction of the CSI 300 stock index futures market impacts the underlying spot market in China based on a theory of feedback trading. Particularly, this paper focuses to explore the interaction between time-varying autocorrelation in returns and conditional volatility in both CSI 300 stock index spot and futures markets by employing an extended EAR-GJR-GARCH model. Results can be used to investigate the issue whether the introduction of index futures trading in China reduces or intensifies the impacts of 'noise' trading in the underlying spot market. The effects of feedback trading in the index futures market will be examined. Moreover, the issue whether the volatility in the spot market increases or decreases after the introduction of index futures trading is addressed as well.

More specifically, there are five main research questions examined in this study as below.

- How does autocorrelation interact with conditional volatility in both CSI 300 stock index spot and futures markets?
- How does autocorrelation react to trading volume as well as past negative and positive economic shocks in both CSI 300 stock index and index futures markets?
- Provided with the evidence on the relation between autocorrelation in spot returns and conditional volatility, does the introduction of CSI 300 index futures reduce or intensify the impacts of feedback trading in the underlying spot market?

- Does the introduction of CSI 300 index futures increase or decrease the volatility of the spot market?
- Provided with the evidence on the relation between autocorrelation in futures returns and conditional volatility, is feedback trading predominant in the CSI 300 stock index futures market?

We use intraday 10-minute data which enhance the understanding of return dynamics because lower frequency data fail to reflect information that occurs in the short term when information adjustment is rapid (Chen, Su and Huang, 2008, pp790). An extended exponential AR (EAR)-GJR-GARCH model is employed to estimate dynamic patterns of time-varying autocorrelation. This model allows for asymmetric impacts on conditional volatility and non-normality distribution. It eases the way of extrapolating the potential non-linear relationship between autocorrelation and conditional volatility.

This paper uses the highest frequency (10-minute) data for this research topic to date. It contributes to the literature in the following three aspects.

First, to our best knowledge, this paper is the first study in the literature investigating how the introduction of index futures trading impacts the underlying spot market in China based on the feedback trading model. Though there have been studies on this topic on the developed stock markets, similar studies on emerging markets are very rare. In particular, there has been no prior study devoted to the Chinese stock market yet. On the other hand, although Yang et al. (2012) and Wen, Wei and Wang (2011) find that information flows intensively between Chinese stock index spot and futures markets, it is still unknown whether information originating from the index futures market brings real development or encapsulates noise to the underlying stock market. This study is dedicated to clarifying this issue.

Second, this paper is the first one to investigate the interaction between autocorrelation and conditional volatility in an emerging index futures market, which can provide evidence on feedback trading in the index futures market of emerging economies. Although previous literature has explored the similar issue in the developed index futures markets such as Antoniou et al. (2005, 2011), there have been no studies focusing on the emerging index futures markets, particularly the newly established Chinese stock index futures market.

Third, the conventional transformed empirical model based upon the theoretical feedback trading model always assumes a linear function between autocorrelation and volatility. As a result, AR-GARCH classes of models are widely employed to examine the impacts of feedback trading in the literature (see, for example, Sentana and Wadhwani, 1992; Koutmos, 1997a; and Antoniou et al., 2005; among others). In contrast, we utilize an exponential AR (EAR)-GARCH model, assuming a nonlinear exponential relation between autocorrelation and conditional volatility, to estimate the dynamic interaction between autocorrelation and volatility and to detect positive feedback trading in this study. The typical priority of EAR model over traditional AR models lies in the fact that the former better fits the observed structure of relationship between autocorrelation and volatility in Chinese markets. Thus, the EAR-GARCH model can yield more efficient and consistent estimates than the conventional models, resulting in empirical results being more robust. Furthermore, to our best knowledge, this study is the first one using the EAR-GARCH model to explain impacts of feedback trading in the literature.

Several important and interesting results are obtained in this study. First, autocorrelation is negatively related to conditional volatility in the spot market only after the introduction of index futures. Thus, there is strong evidence that the introduction of futures intensifies the impact of positive feedback trading in the underlying spot market. The index futures market has a significant impact on the informational efficiency of the spot market.

Second, in the CSI 300 stock index futures market, autocorrelation is negatively related to conditional volatility. Thus, positive feedback trading is predominant in the index futures market. The index futures market attracts noise traders and has the potential of destabilising prices of the underlying spot index market.

Third, trading volume is inversely related to autocorrelation in both spot and futures markets. This supports the proposition that trading volume reflects information to some extent. In addition, bad news affects volatility more intensively than good news in both spot and futures markets. Positive feedback trading is more intense during a price decline than a price rise.

Last, in addition to the impact of positive feedback trading in the spot index market post-futures, market efficiency in the spot market is generally improved after the introduction of futures trading.

Finally, the introduction of the CSI 300 index futures trading is helpful in mitigating the unconditional volatility of the CSI 300 stock index market. One possible reason is that futures trading increase the liquidity of the underlying spot market as more investors are attracted to trade in the spot market.

The remainder of the paper is organised as follows. Section 2 presents literature review. Methodology is discussed in Section 3. Section 4 describes data used in this study and the sample statistics. Section 5 presents the empirical results. Finally, conclusions are drawn in Section 6.

2. LITERATURE REVIEW

Time-invariant autocorrelation in stock returns has been explored by a large body of literature. Using daily or weekly data, French and Roll (1986), Lo and MacKinlay (1988, 1990), Conrad, Kaul and Nimalendran (1991), and Lehmann (1990) find significant and negative autocorrelation in the returns of individual securities. Sias and Starks (1997) find positive autocorrelation for stocks heavily traded by institutions. Cutler, Poterba and Summers (1991) and Lo and MacKinlay (1988) find a significant and positive autocorrelation in daily index returns. It is widely perceived in the literature that autocorrelation in short-term stock returns can be explained by market microstructure-based frictions such as non-synchronous trading, bid-ask spread and transaction costs (Scholes and Williams, 1977; Roll, 1984; Lo and MacKinlay, 1990). Meanwhile, time-varying risk premium also causes serial correlation in stock returns (Fama and French, 1988; Conrad and Kaul, 1988). However, these hypotheses can only yield time invariant autocorrelation (Chen, Su and Huang, 2008).

Recently, time-varying autocorrelation in stock returns has drawn much attention in the literature. Campbell, Grossman and Wang (1993) investigate the relationship between aggregate stock trading volume and the serial correlation of daily stock returns for both stock indexes and individual large stocks. They find the first-order daily return autocorrelation declines with trading volume. Sentana and Wadhwani (1992) propose a feedback trading model to explain the relationship between the autocorrelation in stock returns and conditional volatility. Using daily stock index returns, they employ an Exponential GARCH (EGARCH)-in-mean model to estimate this relationship. They find that autocorrelation has a negative relation with volatility where low volatility yields positive serial correlation in stock returns at short horizons whereas high volatility yields negative serial correlation. They further claim that such sign reversal in stock return autocorrelation is likely to be induced by positive feedback trading prevailing in the market.

LeBaron (1992) implements GARCH and exponential AR (EAR) models on daily and weekly index data. He finds that autocorrelation in returns negatively relates to conditional volatility. Koutmos (1997a) examines the relationship between autocorrelation in daily stock index returns and conditional volatility in several developed stock markets such as Australia, Belgium, Germany, Italy, Japan and the UK. He employs a feedback trading model to explain the time-varying pattern of autocorrelation in index returns. By employing a GARCH-in-mean model, he finds autocorrelation in stock index returns negatively relates to conditional volatility in all the markets examined. There is strong evidence that positive feedback trading induces negative autocorrelation in stock index returns. Koutmos (1997b) investigates the short-term dynamics of stock returns in six emerging stock markets in the Pacific Basin area. By utilising an EAR-TGARCH model, he finds evidence that the first- and second-order autocorrelation in daily stock index returns negatively relates to volatility. The evidence shows that the time-varying pattern of stock return autocorrelation in Asian markets behaves remarkably similar to the major stock markets studied in the literature.

McKenzie and Faff (2003) investigate whether the time-varying autocorrelation in stock returns is affected by return volatility, trading volume, return asymmetry, business cycles and day-of-the-week effect. They use daily data of the S&P 500 index and heavily traded equities and employ a multivariate GARCH approach to obtain the conditional autocorrelation estimates. They find evidence that not only return volatility but also trading volume and market returns are important in explaining the time-varying patterns of return autocorrelation. Antoniou, Koutmos and Pericli (2005) test the hypothesis that the introduction of index futures has increased positive feedback trading in the spot markets of six industrialised nations. Their analysis is based on a feedback trading model in terms of how the autocorrelation in stock index returns is determined by conditional volatility. By using daily data of stock indexes, they find evidence that positive feedback trading is predominant in the spot markets before the introduction of futures trading. In the period following the introduction of futures markets, there is no evidence that positive feedback trading drives short-term dynamics of stock returns. There is no evidence either that positive feedback trading is active in the index futures markets. The authors further claim that futures market helps to stabilise the underlying spot market by reducing the impact of feedback trading and attracting well informed traders into the spot market.

Chen, Su and Huang (2008) study the relationship between the autocorrelation and conditional volatility of the hourly Dow Jones Industrial Index return data from 1974 to 2002. They utilise an exponential asymmetric AR-GARCH model with a generalised error distribution. They find a negative relation between autocorrelation and conditional volatility in hourly returns before 1986. After 1986, the negative relation turns weaker, suggesting it is unstable. Moreover, the authors find negative information shocks have larger impact on volatility after 1986. But asymmetric impact on volatility from negative economic shocks is not revealed by hourly data before the 1987 market crash.

Antoniou, Koutmos and Pescetto (2011) investigate positive feedback trading in four major stock index futures markets in the world. Using daily data of index futures returns, they employ a GARCH-in-mean model to estimate the relationship between autocorrelation and conditional volatility. The evidence shows that there is a negative relation between autocorrelation and conditional volatility in index futures returns, which suggesting some participants engage in positive feedback trading. Moreover, there is evidence that the feedback mechanism exhibits persistence over longer time intervals in the index futures markets. Chang and Shie (2012) explore how autocorrelation impacts volatility in 10 Asian stock markets. By utilising a threshold AR-GARCH model, they obtain an estimation of the volatility pattern with the threshold of a positive or negative prior return autocorrelation. Their model accounts for the asymmetric response of volatility to the autocorrelation in stock returns and accommodates a non-linear relationship between autocorrelation and volatility. The results show different levels of autocorrelation associate with return volatility. The volatility increases as absolute values of autocorrelation increases regardless of whether the autocorrelation is negative or positive. The results for both during- and post-the Asian Financial Crisis periods are consistent.

Furthermore, the issue whether futures trading stabilises or destabilises the underlying spot markets has attracted substantial empirical analysis, though the answer is still not conclusive. Cox (1976) argues that the introduction of futures markets increases the number of traders because index futures are relatively inexpensive and have low margin requirements and low transaction costs. Hence, it increases the channels of information flow. Ross (1989) claims that increased information flow leads to increased price volatility. Price changes in response to a greater volume of information. However, such increased volatility is far from destabilising markets because it is caused by greater informational efficiency in pricing.

Schwert (1990) finds that the growth in stock index futures and option trading has not caused increases in volatility. Edwards (1988a, b) finds that stock return volatility does not rise subsequent to the introduction of index options and index futures. Similar conclusions are reached by Baldauf and Santoni (1991), Becketti and Roberts (1990), Fortune (1989), Pericli and Koutmos (1997), among others. On the contrary, other studies find the introduction of futures trading leads to increases the volatility in spot prices. Moreover, such increase in post-futures volatility is due to an increased information flow rather than destabilising speculation (e.g. Antoniou and Holmes, 1995; Antoniou, Holmes and Priestley, 1998). Further, some studies investigate the impact of futures trading on various underlying assets, e.g. Jochum and Kodres (1998), Fortenbery and Zapata (1997), Nets (1995), among others. Overall, there is a general agreement that the introduction of futures trading does not impact adversely on the underlying market.

However, the literature recognises that futures trading could destabilise the underlying market since it attracts noise traders. De Long, Shleifer, Summers and Waldman (1990a) show that noise traders cause prices to deviate from the fundamental values. De Long, Shleifer, Summers and Waldman (1990b) further claim that if noise traders and rational speculators are both present in the market, rational speculators will 'jump on the bandwagon'. The interaction of noise traders and rational speculators will move prices away from fundamental values in the short horizons. Eventually, rational speculators will liquidate their positions, forcing prices back to the fundamentals. Based on these arguments, Antoniou et al. (2005) and Antoniou et al. (2011) conclude that the introduction of futures market leads to higher volatility and destabilise the underlying market since it can easily attracts both noise traders and rational speculators,. Such increased volatility is caused by the transmission from increased volatility in the futures market due to noise trading, rather than by the increased information flow induced by trading of futures contracts.

Since the CSI 300 stock index futures market has been newly established only for a short period, the number of empirical studies on this market is quite limited. A number of studies generally agree that the CSI 300 stock index futures market does not adversely impact the underlying stock market. See, for example, Zhang, et al. (2011), Wu (2011), Fang and Chen (2011), Guo (2011), among others. However, Yang et al. (2012) reveal that the stock market overshadows the index futures market in China at the very beginning of the futures trading. The volatility of the index futures market can spill into the underlying stock market but the source of such volatility impact is unknown. Hou and Li (2012) find that after one year's development, the CSI 300 stock index futures market can lead the underlying stock market and take a dominant role in the price discovery process in terms of the first moment of return distribution. However, it is not conclusive yet whether the impact from index futures market on the underlying stock market comes from real development brought by the introduction of index futures market or from noise trading induced by index futures.

3. METHODOLOGY

3.1. A Theory of Feedback Trading

Following Shiller (1984), Sentana and Wadhwani (1992), and Koutmos (1997a), we assume that traders in the market consists of two heterogeneous groups. The first group is expected utility optimisers who are governed by risk-return considerations. A fraction of shares of the market portfolio demanded by the first group is given by

$$Q_{1,t} = (E_{t-1}(R_t) - \alpha)/\theta\sigma_t^2 \, . \qquad (1)$$

where R_t is the ex-post rate of return at time t ; $E_{t-1}(.)$ is the expectation based on the information at time *t-1*; α is the rate of return on a risk-free asset; σ_t^2 is the conditional variance of returns (generally perceived as risk) at time t and θ is a fixed coefficient. Note that $\theta\sigma_t^2$ is the required risk premium needed to induce the first group to hold all the shares with $\theta > 0$. Because utility optimisers are risk averse, a rise in expected volatility increases the risk premium needed to induce them to hold all the shares. Note that if all the investors had the same demand function as of Equation (1), then market equilibrium ($Q_t = 1$) would yield the dynamic Capital Asset Pricing Model proposed by Merton (1973):

$$E_{t-1}(R_t) - \alpha = \theta\sigma_t^2. \qquad (2)$$

The second group of investors follow a feedback trading strategy, i.e. they buy or sell shares based on price changes in the past. Thus, their demand function is given by

$$Q_{2,t} = \gamma R_{t-1} \qquad (3)$$

where R_{t-1} is the ex-post rate of return at time *t-1*; γ is the feedback trading parameter which determines the feedback trading strategies. If $\gamma > 0$, feedback traders buy (sell) after price increases (decreases), which is defined as positive feedback trading. If $\gamma < 0$, feedback traders buy (sell) after price decreases (increases), which is defined as negative feedback trading. Positive feedback trading ($\gamma > 0$) is not necessarily irrational or noise trading when a degree of risk aversion declines rapidly with wealth (see, e.g. Black, 1988; De Long, Shleifer, Summers, and Waldman, 1990a; Sentana and Wadhwani, 1992; Koutmos, 1997a). Such trading behaviour is consistent with portfolio insurance strategies and the use of stop-loss orders (Koutmos, 1997a).

Market equilibrium requires that all shares must be held, i.e. $Q_{1,t} + Q_{2,t} = 1$. Thus, combining (1) and (3) yields

$$E_{t-1}(R_t) = \alpha + \theta\sigma_t^2 - \gamma\theta\sigma_t^2 R_{t-1}. \tag{4}$$

This is equivalent to the following regression equation:

$$R_t = \alpha + \theta\sigma_t^2 - \gamma\theta\sigma_t^2 R_{t-1} + \varepsilon_t \tag{5}$$

where ε_t is the forecasting error for the ex-post return R_t. Because the presence of positive feedback trading indicates γ is positive, the term $-\gamma\theta\sigma_t^2 R_{t-1}$ in Equation (5) implies that positive feedback trading induces negative autocorrelation in returns. More importantly, positive feedback trading results in the autocorrelation being time variant. The autocorrelation negatively interacts with conditional volatility. The higher the volatility is, the more negative the autocorrelation becomes. In contrast, negative positive feedback trading

($\gamma < 0$) causes positive autocorrelation in returns. It induces the autocorrelation positively relating to conditional volatility.

Furthermore, Sentana and Wadhwani (1992) points out that feedback trading parameter γ varies with changes in volatility. A portfolio insurance strategy is rational if preferences exhibit risk aversion that declines rapidly with wealth. This implies that the lower the initial level of wealth is, more insurance portfolio selling is likely. Moreover, feedback trading parameter γ depends on the current wealth relative to the current 'subsistence' wealth. This property recognises γ to be inversely related to the wealth. Hence, provided that rational investors expect higher volatility lowers the wealth, a rise in volatility will raise γ and thereby heighten the level of positive feedback trading in the market. Therefore, higher volatility raises the degree of positive feedback trading and thus strengthens the negative autocorrelation. On the other hand, where positive autocorrelation is evident, higher volatility should lessen the observed level of return autocorrelation (McKenzie and Faff, 2003). A negative relationship between returns autocorrelation and conditional volatility provides evidence that positive feedback traders are active in the market.

Third, the higher predictability in returns caused by positive feedback trading does not necessarily imply excess-profits. Higher level of positive feedback trading is always in tandem with higher volatility. This makes it harder for rational risk-averse investors to exploit the predictable pattern of stock prices due to higher risk (Koutmos, 1997a). Thus, during volatile periods positive feedback traders exert a greater influence on price movements. Under this scenario, rational speculators (the first group) would demand higher risk premium on the asset and this allows a larger deviation of the current price from its fundamental value. The interaction between positive feedback traders and rational speculators could lead to price movements that are not warranted by their fundamental values in the short-run (McKenzie and Faff, 2003). Under this scenario, volatility is called ‘destabilised’ because asset prices are driven away from their fundamental values. Eventually, speculators liquidate their position and prices move closer to the fundamental values (Antoniou, Koutmos, and Pescetto, 2011).

3.2. An Extended EAR-GJR-GARCH Model

Feedback trading model as in Equation (5) reveals that a negative relationship between autocorrelation of stock returns and volatility is a necessary and sufficient condition for the dominance of positive feedback trading in the market. Thus, to examine whether positive feedback trading dominates is to investigate whether autocorrelation is negatively related to conditional volatility. A transformed empirical model of Equation (5), which is an AR-GARCH-in-Mean model, is widely used in the literature to examine the predominance of positive feedback trading (see, e.g. Koutmos, 1997a; Antoniou et al., 2005). The mean equation of transformed model contains a composite time-varying autocorrelation term that consists of two parts: one is a constant autocorrelation term, explaining the effect of nonsynchronous trading or market inefficiencies; the other is a time-varying autoregressive term that is a multiplicative product of a parameter and conditional volatility, revealing a dynamic relation between autocorrelation and volatility. Thus, in such a transformed model, a linear relationship between autocorrelation and conditional volatility is assumed.

However, LeBaron (1992) find that an exponential shape better fits the relation between serial correlation and conditional volatility than a linear shape, which is also evidenced in Koutmos (1997b) and Chen et al. (2008). These studies employ an exponential function for the time-varying autoregressive term, instead of a linear function. Following LeBaron (1992), we employ a modified exponential AR (1) Asymmetric GARCH model (EAR (1)-GJR-GARCH (1, 1)) instead of a traditional AR-GARCH-in-Mean model for our empirical study. This model extends the specification in the model developed by Chen et al. (2008) by adding trading volume as an additional exogenous variable in the conditional variance equation. It absorbs properties of EAR-GARCH model of LeBaron (1992) and the GJR-GARCH model proposed by Glosten, Jagannathan and Runkle (1993). More importantly, in contrast to the traditional AR-GARCH-in-Mean model that proposes a linear relationship between the first and second moments of return distributions, the EAR-GJR-GARCH model accounts for the non-linear exponential relation between autocorrelation and conditional volatility (e.g. LeBaron, 1992; Koutmos, 1997b). It captures the short-term dynamics of stock returns in the emerging markets remarkably well (Koutmos, 1997b)[2].

According to Chen et al. (2008), the EAR-GJR-GARCH model accommodates the following stock index and index futures return characteristics: (1) returns are autocorrelated and conditionally heteroskedastic (e.g. Nelson, 1991; Chan, 1992); (2) returns exhibit excess kurtosis (e.g. Bollerslev, 1987; Tse, 1999); (3) returns are impacted by conditional volatility (e.g. Sentana and Wadhwani, 1992; Koutmos, 1997a); (4) past economic shocks have asymmetric effects on conditional volatility (e.g. Glosten et al., 1993; Bohl, Salm, and Schuppli, 2011); and (5) conditional volatility of returns relates to trading volume (e.g. Sentana and Wadhwani, 1992; Mckenzie and Faff, 2003; Kavussanos, Visvikis, and Alexakis, 2008).

We illustrate a model specification with these five return characteristics to accommodate 10-minute spot or futures returns in the following equations:

$$R_t = a_0 + a_1 D_{on} + \left(\phi_0 + \phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}\right) R_{t-1} + \epsilon_t, \tag{6}$$

$$h_t = \alpha_0 + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 I_t \epsilon_{t-1}^2 + \delta_2 V_{t-1} + \delta_3 D_{on}. \tag{7}$$

[2] We depict the relationship between autocorrelation and volatility in Figure 1 which shows a nonlinear exponential curve between autocorrelation and variance for both spot market in post-futures period and futures market. Detailed demonstration is given in Section 4.

where $\epsilon_t \sim iid.[Student-t\ (0, h_t, v)]$.

In Equation (6), R_t is the observed 10-minute logarithmic return series of spot index or index futures at time *t* and a_0 is an intercept of the mean equation. It should be noticed that a_0 is statistically zero when R_t is the returns of index futures. Because futures positions require no initial outlay, the minimum expected rate of return on a futures position is zero (not the risk-free rate) (Antoniou et al., 2011). Hence, when using index futures returns, α in Equation (1) of Section 4.1 equals to zero, which determines a_0 in Equation (6) to be null. D_{on} is an overnight dummy variable that takes a value of 1 if the observation is the overnight non-trading return, zero otherwise. Note that the overnight non-trading return is calculated as the log difference between the first price record in one trading day and the last price record in the previous trading day. The overnight dummy (D_{on}) is included in the conditional variance equation because non-trading period volatility is different from trading period volatility (Chen et al., 2008). Coefficient a_1 measures how the overnight returns are different from 10-minute returns of daytime trading, i.e. the overnight non-trading effect. It should be noted that this non-trading effect can provide information on the market efficiency.

$\phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}$ is a time-varying conditional volatility dependent autoregressive term. Let $\phi_t = \phi_0 + \phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}$, which is the time-varying first-order autocorrelation. ϕ_t is a function of the conditional variance, h_t and the unconditional variance σ^2 of spot or futures returns. Specifically, ϕ_0 measures the time-invariant first-order autocorrelation possibly due to nonsynchronous trading, bid-ask spread, or other market inefficiencies. Note that $\phi_t = \phi_0$

when $\phi_1 = 0$. In this case, the EAR (1)-GJR-GARCH (1, 1) model reduces to the AR (1)-GJR-GARCH (1, 1) model. More importantly, a significant and positive ϕ_1 indicates that time-varying autocorrelation decreases when conditional volatility increases, which further provides evidence that positive feedback trading is predominant in the market. Thus, Equation (6) examines how the first-order autocorrelation relates to conditional volatility. We apply Equation (6) to both spot and futures markets in order to investigate whether positive feedback trading is evident in these two markets.

In Equation (7), the conditional variance, h_t, is a function of the squared innovation at time *t-1*(ϵ_{t-1}^2), the conditional variance at time *t-1* (h_{t-1}), and the overnight dummy (D_{on}). The coefficient α_1 measures how the volatility reacts to the arrival of new information shocks; whereas coefficient β_1 examines how the volatility reacts to the old news persisting in the market.

The GJR asymmetric GARCH term $\delta_1 I_t \epsilon_{t-1}^2$ is included in the conditional variance equation to capture potential asymmetric effects of past positive and negative information shocks on the current conditional volatility. I_t takes the value of 1 if ϵ_{t-1} is positive, and 0 otherwise. Thus, the impact from lagged negative shocks on the conditional volatility is measured by α_1 whereas the impact from lagged positive ones is captured by $(\alpha_1 + \delta_1)$. Such setting is in line with arguments suggesting that good news and bad news impact volatility differently (e.g. French, Schwert, and Stambaugh, 1987). The asymmetric effects are determined by δ_1. Because it is commonly believed that volatility reacts to bad news more intensively than good news, *ceteris paribus*, coefficient δ_1 is expected to be negative. On the other hand, combining with the time-varying conditional volatility dependent autoregressive term in the mean equation, the GJR term tests the proposition that positive feedback trading may become more intense during price declines than price increases (Sentana and Wadhwani, 1992; McKenzie and Faff, 2003). Feedback traders are mostly portfolio insurers and stop-loss order users. Since these strategies are more likely to translate into sell decisions during market declines, one could expect more positive feedback trading during down markets (Koutmos, 1997a, pp634). Hence, positive feedback trading may be more active when stock price suffers a large decline. A significant and negative δ_1 suggests conditional volatility reacts more intensively to lagged negative returns, which may further provide evidence of asymmetric interaction between time-varying autocorrelation and information shocks via the term $\phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}$.

The trading volume of spot index or index futures contracts at time *t-1* (V_{t-1}) is included in the conditional variance equation because trading volume is found to be closely related to volatility (Andersen, 1996). The relationship between them is positive (McKenzie and Faff, 2003); thus the coefficient δ_2 is expected to be positive. Furthermore, as trading volume reflects information (e.g. Fleming and Remolona, 1999), high volume may imply a greater proportion of information-based traders whereas low volume may signify an absence of news, where feedback traders will dominate trading using the information embodied in the past returns (McKenzie and Faff, 2003). Therefore, higher trading volume indicates that more information-based traders are active in the market, which results in lower level of autocorrelation of stock returns. Trading volume seems to be negatively related to the absolute value of autocorrelation. As such, incorporating the variable of trading volume in the conditional variance equation provides evidence of relationship between the time-varying autocorrelation and trading volume through the term $\phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}$.

Residuals (ϵ_t) from Equation (6) follow an identical independent distribution (iid.) with mean zero and conditional variance h_t. Because excess kurtosis in 10-minute spot and futures returns is common as shown in Table 1, the Student's *t*-distribution is assumed for residuals as it can accommodate the fat tail property of the innovations (Bollerslev, 1987). More importantly, the standardised residuals obtained from GARCH models with the traditional assumption of normality appear to be leptokurtic thereby rendering *t*-statistics unreliable (Antoniou et al., 2005). Therefore, assuming the Student's *t* errors makes estimation more efficient than the normal distribution (Susmel and Engle 1994; Tse, 1999).

The Maximum Likelihood Estimation (MLE) method is used to estimate the parameters in the model. For the Student's *t* errors, the contribution to the log-likelihood function for observation *t* is expressed in general terms as:

$$l_t = -\frac{1}{2}log\left(\frac{\pi(v-2)\Gamma\left(\frac{v}{2}\right)^2}{\Gamma\left(\frac{(v+1)}{2}\right)^2}\right) - \frac{1}{2}log\sigma_t^2 - \frac{(v+1)}{2}log\left(1+\frac{(y_t - X_t'\theta)^2}{\sigma_t^2(v-2)}\right) \qquad (8)$$

where $\Gamma(\cdot)$ is the Gamma function, σ_t^2 is the conditional variance, y_t denotes the endogenous variable, X_t' is a vector of exogenous variables, θ is a coefficient vector, and v is the degree of freedom for the Student's *t*-distribution which is estimated endogenously. v controls the tail behaviour. The *t*-distribution approaches to the normal as v increases. The coefficient vector θ is estimated by maximising the log likelihood over the sample period, which can be expressed as

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta) \qquad (9)$$

where T is the sample size. Because the log likelihood function is highly nonlinear, we use the estimation method proposed by Berndt, Hall, Hall and Hausman (1974) to estimate the coefficient vectors.

To further investigate how the introduction of index futures market impacts the underlying spot index market in China in terms for feedback trading, we estimate Equations (6) and (7) using 10-minute spot index returns of pre-futures subsample and post-futures subsample, respectively. That is, the estimation is conducted based on a pre- and a post-futures period, respectively. Moreover, we examine whether positive feedback traders migrate to futures market due to the nature of lower transaction costs and greater leverage potential. Similarly, we estimate Equations (6) and (7) for the index futures market as well.

To further clarify the transitory effects brought about by the event of futures trading as well as to improve testing efficiency, we utilize the full sample of 10-minute spot returns and modify models in Equations (6) and (7) as :

$$R_t = a_0 + a_1 D_{on} + \{\phi_{0,1} H_t + \phi_{0,2}(1 - H_t)\} R_{t-1} + \{\phi_{1,1} H_t + \phi_{1,2}(1 - H_t)\} e^{-\left(\frac{h_t}{\sigma^2}\right)} R_{t-1} + \epsilon_t, \tag{10}$$

$$h_t = \alpha_{0,1} + \alpha_{0,2}(1 - H_t) + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 I_t \epsilon_{t-1}^2 + \delta_2 V_{t-1} + \delta_3 D_{on}. \tag{11}$$

where H_t is the Heaviside indicator function taking the value of 1 in the pre-futures period and zero otherwise. Equations (10) and (11) capture the following characteristics: (i) $\phi_{0,1}$ and $\phi_{0,2}$ measure the time-invariant part of the first-order autocorrelation in pre and post-futures period, respectively. Significant changes from $\phi_{0,1}$ to $\phi_{0,2}$ imply changes in levels of nonsynchronous trading or other market inefficiencies. (ii) $\phi_{1,1}$ and $\phi_{1,2}$ are feedback trading parameters that provide evidence of feedback trading in the spot market in pre and post-futures period, respectively. Significant difference between $\phi_{1,1}$ and $\phi_{1,2}$ implies that feedback trading in the stock market is impacted by the introduction of futures trading. (iii) $\alpha_{0,2}$ measures possible asymmetric response of the unconditional variance to the post-futures period relative to the pre-futures. Significant $\alpha_{0,2}$ indicates that the introduction of futures market affects the unconditional volatility of the underlying spot market.

Furthermore, we are interested in examining the following propositions: (a) If market efficiency is improved in the market besides the effect caused by change in feedback trading, then higher order autocorrelation may also differ between pre- and post-futures periods, particularly reflected by the constant component of autocorrelation (Antoniou et al., 2005). (b) Feedback trading may persist over longer time intervals (Shiller, 1990; Antoniou et al., 2011). The introduction of futures trading may affect the persistence of feedback trading behaviour. To this end, we modify models in Equations (10) and (11) to incorporate the second lag of spot returns. Extended models are proposed as:

$$R_t = a_0 + a_1 D_{on} + \{\phi_{0,1} H_t + \phi_{0,2}(1 - H_t)\} R_{t-1} + \{\phi_{0,3} H_t + \phi_{0,4}(1 - H_t)\} R_{t-2} + \{\phi_{1,1} H_t + \phi_{1,2}(1 - H_t)\} e^{-\left(\frac{h_t}{\sigma^2}\right)} R_{t-1} + \{\phi_{1,3} H_t + \phi_{1,4}(1 - H_t)\} e^{-\left(\frac{h_{t-1}}{\sigma^2}\right)} R_{t-2} + \epsilon_t, \quad (12)$$

$$h_t = \alpha_{0,1} + \alpha_{0,2}(1 - H_t) + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 I_t \epsilon_{t-1}^2 + \delta_2 V_{t-1} + \delta_3 D_{on}. \quad (13)$$

where R_{t-2} denotes spot returns at time *t-2*. In Equation (12), $\phi_{0,3}$ and $\phi_{0,4}$ are parameters representing the constant component of the second-order autocorrelation of spot returns in pre- and post- futures periods, respectively. A change in the statistical significance of $\phi_{0,3}$ and $\phi_{0,4}$ implies that efficiency may be evolved in the spot market in addition to the impact of feedback traders. Thus, estimation of $\phi_{0,3}$ and $\phi_{0,4}$ can be used to test Proposition (a). Second, $\phi_{1,3}$ and $\phi_{1,4}$ measure the persistence of feedback trading over a second time lag. Significant $\phi_{1,3}$ or $\phi_{1,4}$ indicates that feedback traders react to a price trend over a longer period in the stock market in pre- or post- futures period. A significant change from $\phi_{1,3}$ to $\phi_{1,4}$ implies that the introduction of futures impacts the persistence of feedback trading behaviour. Hence, estimation of $\phi_{1,3}$ and $\phi_{1,4}$ can be used in examining Proposition (b). It should be noticed that we construct models in Equation (12) and (13) based on the EAR (*k*)-TGARCH (*p*, *q*) model as proposed in Koutmos (1997b) with $k = 2$.

4. DATA AND SAMPLE STATISTICS

The underlying asset of the CSI 300 index futures contract is the CSI 300 stock index. The expiration (delivery) day of the index futures contract is normally the third Friday of the contract (delivery) month. The contract (delivery) month includes current month, next month and next two calendar quarters which are called quarter-months. There are at least four contracts being traded in each calendar month. On the delivery day, the futures contract is cash settled. The contract size is the index value of CSI300 multiplied by RMB 300. Initial margin requirement is set at 12% of the contract value. The tick size of each contract is 0.2 point.

We collect 10-minute price observations for the CSI300 stock index and index futures prices. All the data are obtained from Thomson Reuters Tick History (TRTH). The reason why we use the high frequency data is that lower frequency data fail to reflect information that occurs in the short horizon when the speed of information adjustments is relatively rapid (Chen, Su and Huang, 2008). Thus, study on the intraday returns can enhance the understanding of stock return dynamics.

The sample period for the CSI300 spot index is from April 16th, 2008 to April 16th, 2012. We further divide the sample into two subsamples in order to investigate how the introduction of the futures trading impacts the underlying spot market. The first subsample, the pre-futures period, is from April 16th, 2008 to April 15th, 2010. The second subsample, the post-futures period, is from April 16th, 2010 to April 16th, 2012. For the 10-minute index observations, price records from 9:30 a.m. to 11:30 a.m. and from 1:00 p.m. to 3:00 p.m. are picked in a trading day. After eliminating weekends and holidays, we end up with 25450 10-minute price observations for the full sample period of CSI 300 spot index. Additionally, we collect 25450 10-minute observations of trading volume for the CSI 300 stock index in the whole sample period. The 10-minute trading volume of the CSI 300 stock index is the total number of shares traded in every 10 minutes of a trading day for 300 component stocks consisting of the index in Shanghai and Shenzhen stock exchanges. We take the natural logarithms of trading volume to remove low frequency variations in the series (Campbell et al., 1993). Unit root tests suggest volume series are stationary[3].

The sample period for the CSI300 index futures is from May 17th, 2010 to April 16th, 2012. The first month of data for the index futures are excluded because we give one month's time for the newly established index futures market to stabilise. To construct a continuous time series of futures prices, we select prices of the most liquid futures contracts. In each calendar month, prices of the futures contract expiring in the current month are chosen until five working days before its expiration. Then, we switch to prices of the contract which expires in the next calendar month for other days in the month. For the 10-minute futures price

[3] Augmented Dickey-Fuller and Phillips-Perron tests confirm the stationarity of volume series. To conserve space, results are not reported but available upon request.

observations, price records from 9:20 a.m. to 11:20 a.m. from 1:00 p.m. to 3:10 p.m. are used. After eliminating the obsolete data from weekends and holidays, we get 12513 10-minute price observations of the CSI300 index futures for the sample period. In addition, 12513 intraday 10-minute observations of trading volume for the index futures contracts are also collected[4].

Both 10-minute returns of the CSI300 spot index and futures are calculated as R_t = 100(log P_t – log P_{t-1}) where P_t is the 10-minute price observation at time t[5]. Additionally, among the intraday 10-minute returns, we compute 971 overnight non-trading spot returns and 463 overnight non-trading futures returns based on the prior day’s closing price and the following day’s opening price. Note that this computation of overnight return complies with the traditional measurement of close-to-open returns.

Descriptive statistics for the intraday 10-minute returns of the CSI300 spot and futures markets are provided in Table 1. The statistics reported in this table are the mean (μ), the standard deviation (σ), the measure of skewness (*S*), the measure of kurtosis (*K*), the Kolmogorov-Smirnov statistic (*D*), and the Ljung-Box (LB) statistic for 12 lags.

[Insert Table 1 about here]

A few observations can be made from Table 1. First, the standard deviation of the spot return series in the pre-futures period is much larger than the post-futures period. This raises doubt that the introduction of the futures trading might decrease the volatility of the spot market, which will be further explored in the subsequent sections.

[4] Similar as trading volume of stock index, 10-minute trading volume of index futures is taken in the form of natural logarithms. Moreover, they are also stationary as suggested by unit root tests.
[5] Both spot and futures return series are statistically stationary as suggested by ADF and PP unit root tests. Results are available upon requests.

Second, the measures of skewness and kurtosis indicate that the return series of spot and futures markets are not normally distributed. More specifically, excess kurtosis is pronounced in both spot and futures returns. Likewise, the Kolmogorov-Smirnov statistics suggest significant deviations from the normality. Thus significant non-normality and excess kurtosis of returns need to be accounted for when empirical models are constructed. Additionally, non-normality may be attributed to temporal dependencies in the moments of return series.

Third, the Ljung-Box (LB) statistics provide evidence of temporal dependencies in the first moment of the distributions of 10-munite spot and futures returns. However, it is not clear to what extent nonsynchronous trading or market inefficiencies contribute to first-moment dependencies in intraday 10-minute spot and futures returns. Moreover, the LB statistic fails to detect any sign reversals in the autocorrelations due to feedback trading (Antoniou, Koutmos, and Pericli, 2005). This simply shows that temporal dependencies in the first moment are present.

Last, evidence on temporal dependencies in the higher moments is provided by the LB statistics applying to squared returns. For both squared spot and futures returns in 10-minute time intervals, the LB statistics are all significant. Compared with significance of the LB statistics calculated for the return level, higher moment temporal dependencies are more evident. This is an empirical regularity encountered in almost all financial time series, especially in high frequency data (Antoniou et al., 2005). What we need to clarify is how two types of temporal dependencies are linked with each other, i.e. whether and how autocorrelation and volatility are linked due to the presence of feedback trading behaviour.

[Insert Figure 1 about here]

Figure 1 plots the dynamic relation between autocorrelation and conditional volatility in the CSI 300 markets. A rolling-window estimation procedure is utilised to calculate autocorrelation and conditional variance. The autocorrelation and conditional variance are initially computed using the first 100 10-minute returns. This procedure is then repeated using a moving window of 100 observations and moving step size is set as one observation point at a time. A series of different pairs of autocorrelation and corresponding variance are obtained and plotted. To better visualise the association between first-order autocorrelation and conditional volatility, a fitted line is added to each panel of Figure 1 by fitting the coefficients estimated by the EAR(1)-GJR-GARCH(1,1) model in Equations (6) and (7) to different pairs of autocorrelation and variance[6].

Panel A of Figure 1 plots the relation between first-order autocorrelation and volatility in pre-futures period. We cannot detect any clear linear or nonlinear relationship from this plot where autocorrelation clumps at lower values of variance and drifts far away from them. This raises a doubt that before future trading is introduced, the fist-order autocorrelation of the CSI 300 index spot returns may not be significantly impacted by conditional volatility. In addition, any linear or nonlinear shape may not describe the relation between autocorrelation and volatility in this sample period very well. However, Panel B clearly shows a negative exponential relation between autocorrelation and volatility in post-futures period, suggesting an exponential shape should better describe the relation between autocorrelation and volatility in this sample period. The visualization of Panel C for index futures market is quite similar to Panel B, where a negative nonlinear exponential relation is obviously depicted. Therefore, Panels B and C in Figure 1 suggest, first, a potential negative exponential relation between first-order autocorrelation and volatility may exist in post-futures period of the CSI 300 spot market as well as in the CSI 300 index futures market, which will be further examined in the next section; second, an exponential expression of function can better fit the relation between serial correlation and conditional volatility than a linear expression in the

[6] Detailed estimation results of Equations (6) and (7) are reported in Section 5.

case of the CSI 300 markets. This is in accordance with arguments made by LeBaron (1992) and Chen et al. (2008). Hence, the EAR-GJR-GARCH model utilised in this study could yield more efficient and consistent estimates than the transformed empirical model of Equation (5) as in Antoniou et al. (2005) assuming a linear relationship between autocorrelation and volatility with respect to 10-minute returns of the CSI 300 markets. Results of the EAR model can be attributed to theoretical feedback trading model of Equation (5), which is used to detect positive feedback trading.

5. EMPIRICAL RESULTS

In this section, we report the empirical results and discuss our findings.

5.1. Feedback trading in the CSI 300 stock index market

Table 2 reports the estimation results of Equations (6) and (7) using 10-minute spot index returns for both the pre- and post-futures periods.

First, we look at the results of the mean equation in Table 2. Estimate of coefficient a_1 for the pre-futures period is not statistically significant at any conventional level; in contrast, estimate of a_1 for the post-futures period is significant at the 1% level. Hence, the commencement of index futures trading enhances the non-trading effect on intraday 10-minute spot index returns.

[Insert Table 2 about here]

Estimate of φ_0 in Equation (6) for the pre-futures period is not statistically significant at any conventional level; however, estimate of φ_0 for the post-futures period is statistically significant at the 1% level. This suggests that the time-invariant component of the first-order autocorrelation for 10-minute spot returns becomes more evident after the futures market begins to trade. Because the constant component of the first-order autocorrelation associates with market efficiency, difference in statistical significance of φ_0 between pre and post-futures period implies that spot market may be less efficient after futures market is introduced based on the 10-minute returns. Moreover, φ_0 for the post-futures is negative (-0.090), suggesting bid-ask spread may take effect in the spot market in the post-futures period with regard to 10-minute returns (Tsay, 2010).

To assess the relation between time-varying autocorrelation and conditional volatility, we look at estimate of φ_1 in Equation (6). Table 2 shows that estimate of φ_1 for the pre-futures period is not statistically significant. Thus the first-order autocorrelation in 10-minute spot returns is not related to conditional volatility before trading of futures contracts. The first-order autocorrelation turns out to be time-invariant in the pre-futures period. Thus we conclude that there is no evidence of feedback trading in the spot market before futures market is introduced.

However, the estimate of φ_1 for the post-futures period is significant at the 1% level and is positive (0.192). Hence, the first-order autocorrelation in 10-minute spot returns is negatively related to conditional volatility after the introduction of futures market. This provides strong evidence that positive feedback trading is predominant in the stock market in the post-futures period. Because positive feedback trading is not evident in pre-futures period, we can conclude that the introduction of CSI 300 index futures market gives rise to predominance of positive feedback trading in the CSI300 stock index market. It should be also noteworthy that it is the presence of positive feedback trading in the post-futures period that may strengthen the level of constant autocorrelation in the spot returns in the same period. This is confirmed by significant estimate of post-futures φ_0. Our finding is in sharp contrast to empirical results on major developed markets reported by Antoniou et al. (2005). Rather than reducing the impact of positive feedback trading on the underlying market, the introduction of CSI 300 stock index futures heightens it and makes the underlying market less informationally efficient. This raises doubt that the futures market may attract feedback traders as well as rational speculators due to the lower transaction costs and the greater leverage potential.

Second, we check the results of the conditional variance equation in Table 2. Estimates of α_1 and β_1 in Equation (7) for both pre- and post-futures periods are statistically significant at the 1% level. Thus, regardless of the introduction of futures trading, volatility of 10-minute spot returns is impacted by the arrival of new shocks as well as the persistence of old news.

Regarding asymmetric volatility effect brought about by positive and negative information shocks, we find estimates of δ_1 in Equation (7) for pre- and post-futures periods are both statistically significant at the 1% level. More importantly, both δ_1 for pre- and post-futures periods are estimated to be negative (-0.115 for pre-futures while -0.076 for post-futures). This means that intraday 10-minute spot volatility reacts more intensively to lagged bad news than lagged good news regardless of inducement of futures trading. It further suggests that the first-order autocorrelation in 10-minute spot returns diminishes more intensively in an event of price declines than price advances in post-futures period because there is a significant inverse relationship between autocorrelation and volatility in the same period. Thus, positive feedback trading becomes more active during market downturns than market upturns after the introduction of stock index futures.

Furthermore, estimate of δ_2 in Equation (7) is statistically significant at the 1% level only for the post-futures period. The estimate is positive (0.179), which suggests intraday trading volume of stock index increases intraday volatility after index futures market is introduced. Moreover, since estimate of post-futures φ_1 in Equation (6) is statistically significant and positive, intraday trading volume is negatively related to the first-order autocorrelation in intraday spot returns after futures trading begins via the term $\phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}$. The result is in line with the argument proposed by McKenzie and Faff (2003) that high trading volume can reduce the level of autocorrelation as volume reflects information embodied in the transactions. In addition, it should be noticed that the introduction of futures trading enhances the relation between trading volume and volatility. This may be due to the fact that futures market increases the flow of information to the underlying market. Since trading volume is deemed as a proxy of information-based trading (McKenzie and Faff, 2003), increased information flow can result in a significant and positive relationship between trading volume and volatility in the underlying spot market.

Estimates of δ_3 in Equation (7) for pre- and post-futures periods are both statistically significant at the 1% level. Hence, regardless of impact of futures trading, overnight non-trading period volatility is found to be different from trading period volatility in terms of 10-minute spot returns.

[Insert Table 3 about here]

Table 3 reports the estimation results of Equations (10) and (11) to detect transitory effects in 10-minute spot returns incurred by the introduction of futures trading. Results in Table 3 are similar as Table 2, confirming the findings reported earlier that the overall informational efficiency in the spot market has decreased and positive feedback trading becomes predominant in the market after futures market is introduced. Specifically, we can observe in Table 3 that (i) $\varphi_{0,1}$ is not statistically significant at any conventional level while $\varphi_{0,2}$ is significant at the 1% level and is negative (-0.086). Such significant change from $\varphi_{0,1}$ to $\varphi_{0,2}$ implies that market efficiency in the post-futures period is lower than the pre-futures period. (ii) $\varphi_{1,1}$ is not statistically significant at any conventional level whereas $\varphi_{1,2}$ is significant at the 5% level and is positive (0.132). Significant and positive $\varphi_{1,2}$ indicates positive feedback trading is present in the post-futures period, which may be caused by the introduction of futures trading. (iii) $\alpha_{0,2}$ is significant at the 1% level and is negative (-0.779), indicating unconditional variance of 10-minute spot returns decreases in the post-futures period. Thus the introduction of futures has resulted in lower volatility of the underlying spot market.

[Insert Table 4 about here]

Table 4 reports estimation results of Equations (12) and (13). To examine whether market efficiency is improved in addition to the impact of feedback trading in the spot index market, we look at estimates of $\varphi_{0,3}$ and $\varphi_{0,4}$ in Equation (12). $\varphi_{0,3}$ is statistically different from zero at the 1% level while $\varphi_{0,4}$ is not statistically different from zero at any conventional level. Hence, the constant component of the second-order autocorrelation significantly changes from pre- to post-futures periods. This implies that efficiency in the spot market may be more generally improved regardless of the impact of positive feedback trading in the post-futures period. Second, we find both the estimate of $\varphi_{1,3}$ or $\varphi_{1,4}$ are not significant at any conventional level in Table 4. Thus, feedback trading does not operate over the second lag in either pre- or post-futures period. There is no evidence on persistence of feedback trading over longer time intervals in pre- or post-futures period with respect to intraday spot returns.

[Insert Table 5 about here]

To test the robustness of the results to different window specifications around the contract introduction event, we re-estimate the model in Equations (10) and (11) using 0.5-, 1-, and 1.5-year windows. Tighter windows are perceived to provide a more rigorous test of the feedback trading story (Antoniou et al., 2005). Estimation results on a series of window testings are shown in Table 5. As can be seen from Table 5, the results remain qualitatively the same when the 1- and 1.5-year windows are used. For the 0.5-year window, there is no clear evidence that positive feedback trading is evident in the post-futures period. However, the additional findings from 1- and 1.5-year windows support positive feedback trading being more noticeable in the period following index futures introduction.

In sum, in the CSI 300 stock index market, there is a significant change in the constant component of the first-order autocorrelation in the 10-minute spot returns from pre to post-futures periods. This implies that the introduction of futures market impacts the efficiency of underlying spot market by intensifying the effect of bid-ask spread. More importantly, there is no evidence of positive feedback trading in the pre-futures period; nonetheless, we find autocorrelation is negatively related to conditional volatility in the post-futures period. Hence, there is some strong evidence that positive feedback trading is predominant after the introduction of futures trading in China. It is further concluded that the introduction of futures gives rise to the predominance of positive feedback trading in the underlying spot market, making the spot market less informationally efficient. In addition, the unconditional volatility of 10-minute spot returns decreases in the post-futures period, implying that the futures is helpful in reducing volatility of the underlying spot market. This may be attributed to the fact that futures trading improves the liquidity of the underlying stock market and leads to reduced volatility in the stock market.

We find strong evidence that conditional volatility reacts more intensively to bad news than good news in the spot market in both pre- and post-futures periods. Moreover, positive feedback trading becomes more active in an event of market downturns relative to market upturns after the introduction of stock index futures trading. This is in line with McKenzie and Faff (2003). Moreover, we find a critical change in relationship between intraday trading volume and conditional volatility in the spot market from pre- to post-futures periods, which may be caused by increased information flow from futures trading. Additionally, intraday trading volume of stock index is able to lessen the first-order autocorrelation in 10-minute spot returns in post-futures period. This result is consistent with the literature finding that trading volume reflects information to some extent.

Finally, the efficiency of the spot market has improved after the introduction of the index futures market, though the impact of positive feedback trading in the post-futures period has intensified. Moreover, there is no evidence that positive feedback trading persists over longer time intervals.

5.2. Feedback trading in the CSI 300 stock index futures market

Above findings on stock index market seem to suggest that feedback trading is likely to be predominant in the futures market due to some of its features such as lower transaction costs and greater leverage potential. According to Antoniou et al. (2005), the introduction of futures could attract both rational speculators as well as positive feedback traders. This may destabilize volatility where futures prices are driven away from their fundamental values. This impact can be transmitted to the spot market through the process of arbitrage and consequently result in spot prices swaying from their fundamentals. In this section, the destabilising effect is investigated by estimating the EAR (1)-GJR-GARCH (1, 1) model in Equations (6) and (7) using 10-minute futures returns. The results are shown in Table 6.

[Insert Table 6 about here]

First, the estimate of φ_0 is negative (-0.085) and statistically different from zero at the 1% level. The significant constant part of the first-order autocorrelation indicates that market inefficiencies are evident in the futures market. The negativity implies that the bid-ask spread may play a significant role.

Second, the estimate of φ_1 is statistically significant at the 1% level and is positive (0.156). Hence, the first-order autocorrelation in 10-minute futures returns is time-varying, which negatively relates to conditional volatility. This renders strong evidence that positive feedback trading is predominant in the futures market.

Third, the conditional volatility reacts more intensively to lagged negative information shocks than lagged positive ones in the index futures market, as indicated by the estimate δ_1 (-0.022). δ_1 is negative and significant at the 1% level. Given the inverse relationship between volatility and autocorrelation, the first-order autocorrelation decreases more intensively during price declines than price rises in the futures market. Therefore, positive feedback trading becomes more active in the event of a market downturn than a market upturn in the index futures market.

Furthermore, parameter δ_2 in the conditional variance equation is statistically significant at the 5% level and is positive (0.146), indicating intraday trading volume is positively related to conditional volatility in the index futures market. This provides evidence that there is a positive correlation between volume and volatility (Sentana and Wadhwani, 1992; Kavussanos et al., 2008). Moreover, since feedback trading parameter φ_1 is significant and positive, the intraday trading volume of contracts is negatively related to the first-order autocorrelation in intraday futures returns via the term $\phi_1 e^{-\left(\frac{h_t}{\sigma^2}\right)}$. Thus, it supports the proposition that trading volume reflects information in transactions.

To sum up, regarding the index futures market, the stock index futures market attracts positive feedback traders to implement their trend chasing strategies. This result is in line with that from the underlying spot market in the post-futures period. Rather than expanding the information channels and improving informational efficiency for the underlying market, the futures market plays a role in attracting noise traders and has the potential of destabilising asset prices of the underlying market through the process of arbitrage.

Furthermore, similar to the spot market, positive feedback trading is more intense during a price decline than during a price rise in the futures market. Meanwhile, the trading volume of index futures contracts is found negatively related to the autocorrelation in futures returns, which supports that trading volume somehow reflects information-based trading.

6. CONCLUDING REMARKS

Although the issue on whether the introduction of futures trading impacts the underlying spot markets in terms of feedback trading model in the developed economies has been well documented in the literature, there is hardly any evidence from the emerging markets. This study is the first to investigate how the introduction of the index futures impacts on the feedback trading in the underlying spot market in China through examining the relationship between time-varying autocorrelation and conditional volatility in stock returns. Additionally, we explore the effects of feedback trading in the Chinese stock index futures market, which has not been examined in the literature either. The issue whether the volatility of spot market increases or decreases after the introduction of futures trading is also examined.

Based on an extended EAR-GJR-GARCH model with a Student-*t* distribution in error terms by using high-frequency 10-minute data, a few interesting findings have been obtained.

First, the introduction of index futures somehow mitigates the unconditional volatility of the spot index market. This may be due to that the trading of CSI 300 index futures increases liquidity of the underlying spot market as it attracts more investors to the market. However, it is strongly evident that positive feedback traders are proactive in the spot market after the introduction of index futures market. Since there is no evidence on positive feedback trading in the spot market before the futures was introduced, we can conclude the trading of index futures is likely to induce trend-chasing strategies prevailing in the spot market. This implies that informational efficiency of the spot market may be impacted by the introduction of futures. Meanwhile, the index futures market is found to be informationally inefficient as it attracts positive feedback traders itself. Thus, it is revealed that the positive feedback trading is predominant in both spot and futures markets in China.

Second, the improvement of information efficiency in the spot market cannot be warranted by introducing the index futures because the information coming from the futures market contains 'noise'. Rather than expanding the information channels and improving informational efficiency in the underlying market, the CSI 300 index futures market attracts noise traders to transact futures contracts in the market. The interaction of rational speculators and 'noise' traders in the futures market destabilises futures prices first; then the destabilising effect is transmitted to the underlying spot market through the process of arbitrage. As a result, index prices are driven away from their fundamentals. Moreover, positive feedback trading existing in the spot market may drive spot prices from fundamentals even further.

Third, trading volume is inversely related to autocorrelation in returns in both spot and futures markets. Higher volume may imply a greater proportion of information-based trades. This in turn leads lower autocorrelation of returns. The result is consistent with the literature that trading volume reflects information embodied in the transactions. Furthermore, bad news impacts volatility more intensively than good news in both spot and futures markets. The asymmetric response of autocorrelation to information shocks implies that a price decline may result in more active positive feedback trading in the market than a price rise.

It should be noted that our results are robust in two aspects. First, the results of 0.5-, 1- and 1.5-year window tests have confirmed that key findings are robust. Second, we have also conducted the investigation using data in other time frequencies rather than 10-minute and similar results can be obtained[7].

In this study, changes to the autocorrelation are driven solely by changes in the conditional variance of the series. McKenzie and Faff (2003) claim that ignoring a time-variant covariance component of the autocorrelation estimate may suppress a potentially importance source of variation in autocorrelation. Thus, a future study could be conducted by updating the model in this study to a multivariate GARCH model, which can generate estimates of autocorrelation derived by a time –varying covariance matrix between asset returns and their lags. The potential determinants of autocorrelation can be examined in this way.

[7] Results are available upon request.

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Table 1. Descriptive Statistics of Intraday 10-minute Rates of Return for the CSI300 Stock Index and Futures

	10-minute stock returns (16/4/08-16/4/12)	10-minute stock returns (16/4/08-15/4/10)	10-minute stock returns (16/4/10-16/4/12)	10-minute futures returns (17/5/10-16/4/12)
μ	-0.0012	-0.0003	-0.0022	-0.0008
σ	0.365	0.441	0.266	0.267
S	0.571*	0.686*	-0.231*	0.361*
K	38.796*	34.478*	11.968*	15.062*
D	0.260*	0.231*	0.298*	0.303*
$LB(12)$	116.566*	102.140*	32.381*	37.926*
$LB^2(12)$	146.999*	40.058*	199.516*	232.760*

Notes: This table reports the sample statistics of 10-minute returns for the CSI300 stock index and futures. Note that the full sample period of the stock index is from 16/4/08 to16/4/12.The periods of subsample 1 and 2 of the spot are from 16/4/08 to 15/4/10 and from 16/4/10 to 16/4/12, respectively. The sample period of the index futures is from 17/5/10 to 16/4/12. μ—mean; σ—standard deviation; S—skewness; K—kurtosis; D—Kolmogorov-Smirnov statistic. $LB(n)$and $LB^2(n)$ are the Ljung-Box statistics for R_t and R^2_t, respectively. The Ljung-Box statistics are distributed as χ^2 with n degrees of freedom, where n is the number of lags. The Kolmogorov-Smirnov statistic is calculated as $D_n = |F_n(R)-F_0(R)|$ where $F_n(R)$ is the empirical cumulative distribution of R_t, and $F_0(R)$ is the postulated theoretical distribution of R_t. In this table, the theoretical distribution of R_t is set as normal distribution. The Ljung-Box statistic for n lags is calculated as $LB(n)=T(T+2)\sum_{j=1}^{n}(\rho_j^2/T-j)$where ρ_j is the sample autocorrelation for j lags and T is the sample size. *, **, and *** denote the significance at the 1%, 5% and 10% levels, respectively.

Table 2. Maximum likelihood estimates of the EAR (1)-GJR-GARCH (1, 1) model for 10-minute CSI 300 spot returns in pre- and post-futures periods

	Pre-futures period (16/4/08-15/4/10)	Post-futures period (16/4/10-16/4/12)
Parameters	Eqs. (6) & (7)	Eqs. (6) & (7)
a_0	0.001 (0.50)	-0.004*** (-1.87)
a_1	0.009 (0.37)	-0.040* (-2.65)
φ_0	-0.002 (-0.07)	-0.090* (-3.64)
φ_1	0.040 (0.81)	0.192* (3.54)
α_0	-3.554* (-6.96)	-6.848* (-12.37)
α_1	0.259* (13.76)	0.144* (11.73)
β_1	0.624* (41.00)	0.711* (51.43)
δ_1	-0.115* (-5.93)	-0.076* (-6.09)
δ_2	-0.050 (-1.07)	0.179* (3.51)
δ_3	3.223* (39.20)	3.017* (38.37)
v	6.235* (21.02)	6.957* (17.85)

Notes: This table reports estimation results based on Equations (6) and (7) where 10-minute spot returns are used. The estimation is conducted for a pre- and a post-futures period, respectively. The pre-futures period is from 16/4/08 to 15/4/10, which is subsample 1 of 10-minute spot returns, whereas the post-futures period is from 16/4/10 to 16/4/12, which is subsample 2 of 10-minute spot returns. The MLE method is used to obtain estimates where BHHH algorithm is utilised for maximisation. Figures in parentheses (.) are *t*-statistics. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Maximum likelihood estimates of the extended EAR (1)-GJR-GARCH (1, 1) model for 10-minute CSI300 spot returns in full sample period

Eq. (10)	Estimates	*t*-Statistic
a_0	-0.002	(-1.22)
a_1	-0.027^{**}	(-1.99)
$\varphi_{0,1}$	-0.002	(-0.11)
$\varphi_{0,2}$	-0.086^{**}	(-2.55)
$\varphi_{1,1}$	0.060	(1.11)
$\varphi_{1,2}$	0.132^{**}	(2.44)
Eq. (11)		
$\alpha_{0,1}$	-4.408^{*}	(-11.98)
$\alpha_{0,2}$	-0.779^{*}	(-22.61)
α_1	0.204^{*}	(18.09)
β_1	0.655^{*}	(60.96)
δ_1	-0.095^{*}	(-8.21)
δ_2	0.032	(0.95)
δ_3	3.091^{*}	(54.57)
v	6.565^{*}	(27.96)

Notes: This table reports estimation results based on Equations (10) and (11) where 10-minute spot returns are used. The estimation is conducted for the full sample period of 10-minute spot returns, i.e. from 16/4/08 to 16/4/12. The MLE method is used to obtain estimates where BHHH algorithm is utilised for maximisation. Figures in parentheses (.) are t-statistics. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4. Maximum likelihood estimates of the extended EAR (2)-GJR-GARCH (1, 1) model for 10-minute CSI300 spot returns in full sample period

Eq. (12)	Estimates	*t*-Statistic
a_0	-0.002	(-1.14)
a_1	-0.024***	(-1.81)
$\varphi_{0,1}$	-0.006	(-0.28)
$\varphi_{0,2}$	-0.089**	(-2.58)
$\varphi_{0,3}$	-0.052*	(-2.99)
$\varphi_{0,4}$	-0.008	(-0.27)
$\varphi_{1,1}$	0.074	(1.35)
$\varphi_{1,2}$	0.137**	(2.45)
$\varphi_{1,3}$	-0.033	(-0.68)
$\varphi_{1,4}$	0.013	(0.28)
Eq. (13)		
$\alpha_{0,1}$	-4.457*	(-12.13)
$\alpha_{0,2}$	-0.774*	(-22.44)
α_1	0.199*	(17.94)
β_1	0.656*	(61.04)
δ_1	-0.091*	(-8.05)
δ_2	0.037	(1.11)
δ_3	3.077*	(54.35)
v	6.381*	(28.14)

Notes: This table reports estimation results based on Equations (12) and (13) where 10-minute spot returns are used. The estimation is conducted for the full sample period of 10-minute spot returns, i.e. from 16/4/08 to 16/4/12. The MLE method is used to obtain estimates where BHHH algorithm is utilised for maximisation. Figures in parentheses (.) are t-statistics. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. Maximum likelihood estimates of the extended EAR (1)-GJR-GARCH (1, 1) model for 10-minute CSI300 spot returns in 0.5-, 1-, and 1.5-year windows

Parameters	0.5-year window	1-year window	1.5-year window
Eq. (10)			
a_0	-0.0002 (-0.01)	0.005** (2.23)	0.001 (0.70)
a_1	-0.008 (-0.32)	0.015 (0.98)	-0.006 (-0.44)
$\varphi_{0,1}$	-0.024 (-0.49)	-0.053*** (-1.74)	-0.024 (-1.09)
$\varphi_{0,2}$	-0.038 (-0.73)	-0.081** (-2.29)	-0.080** (-2.41)
$\varphi_{1,1}$	0.046 (0.45)	0.075 (1.02)	0.076 (1.28)
$\varphi_{1,2}$	0.069 (0.57)	0.145*** (1.95)	0.127** (2.16)
Eq. (11)			
$\alpha_{0,1}$	-7.187* (-8.02)	-8.355* (-11.51)	-7.434* (-14.17)
$\alpha_{0,2}$	0.233* (3.66)	-0.116** (-2.29)	-0.534* (-12.62)
α_1	0.186* (8.85)	0.182* (14.08)	0.199* (16.67)
β_1	0.676* (31.87)	0.747* (63.30)	0.704* (67.15)
δ_1	-0.122* (-5.89)	-0.124* (-9.52)	-0.111* (-9.08)
δ_2	0.224* (2.76)	0.314* (4.83)	0.276* (5.82)
δ_3	2.936* (27.57)	3.004* (33.75)	3.011* (44.62)
v	8.994* (9.72)	7.949* (15.38)	6.993* (22.84)

Notes: This table reports estimation results based on Equations (10) and (11) where 10-minute spot returns are used. Equations (10) and (11) are re-estimated using 0.5-, 1-, and 1.5-year windows, respectively. Windows are based on the day of the introduction of the futures contract, i.e. 16/4/10. Sample period for 0.5-year window is from 15/10/09 to 16/10/10. Sample period for 1-year window is from 15/4/09 to 16/4/11. Sample period for 1.5-year window is from 15/10/08 to 16/10/11. The MLE method is used to obtain estimates where BHHH algorithm is utilised for maximisation. Figures in parentheses (.) are t-statistics. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

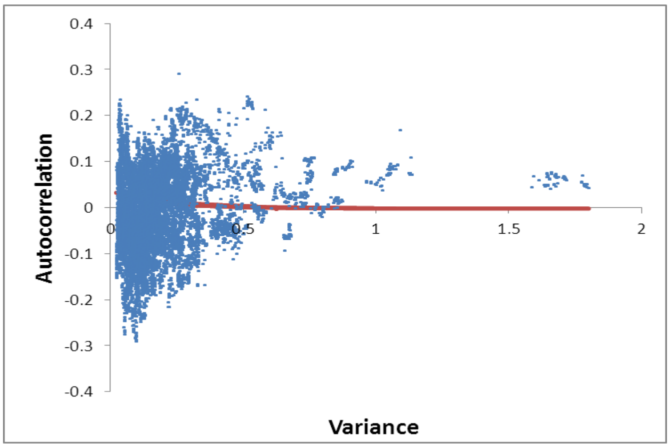
Table 6. Maximum likelihood estimates of the EAR (1)-GJR-GARCH (1, 1) model for 10-minute CSI 300 index futures returns

Eq. (6)	Estimates	*t*-Statistic
a_1	0.047*	(4.74)
φ_0	-0.085*	(-4.62)
φ_1	0.156*	(3.66)
Eq. (7)		
α_0	-8.602*	(-12.80)
α_1	0.078*	(10.51)
β_1	0.897*	(122.56)
δ_1	-0.022*	(-2.77)
δ_2	0.146**	(2.32)
δ_3	4.590*	(11.00)
v	3.620*	(27.18)

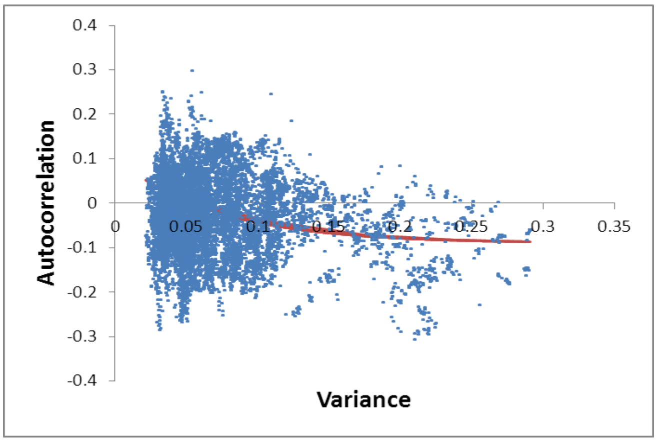
Notes: This table reports estimation results based on Equations (6) and (7) where 10-minute index futures returns are used. The sample period for 10-minute futures returns is from 17/5/10 to 16/4/12. The estimate of a_0 in Equation (6) is intuitively zero thereby it is not reported in this table. The MLE method is used to obtain estimates where BHHH algorithm is utilised for maximisation. Figures in parentheses (.) are *t*-statistics. *, **, and *** denote significance at the 1%, 5%, and 10% levels, respectively.

Figure 1. Relation between return autocorrelation and variance in CSI 300 index spot and futures markets

Panel A: Pre-futures period of spot market



Panel B: Post-futures period of spot market



Panel C: Index futures market