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FACULTY OF LAW, ARTS & SOCIAL SCIENCES
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Essays on the Chinese Financial Markets

By

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ABSTRACT

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This thesis examines the stability of the Chinese stock market from three different aspects. In the market microstructure literature, the topic of the price-volume relation has been discussed for long time because it is potentially important in understanding how information is transmitted to the market as well as embedded in stock prices. However, the results in Chinese stock market are not consistent with the theoretical prediction since nonlinear Granger causality between price and volumes can not be detected. Then, we show that non-tradable shares matter on the stock market and affect the price-volume relation. Our findings indicate that the existence of liquidity constraint affects information flow, and in turn, result in different casual patterns of price-volume relation.

Secondly, we use the aggregate level data to investigate the impact of fund investors' behaviour on market prices since recently the Chinese government implemented the policy to launch a number of mutual funds. In the literature the evidence of the impact of institutional trading on the stock prices is not conclusive. Our empirical findings do not support the hypothesis that investment fund trading destabilizes the prices at the market level.

Finally, we explore the impact of warrant listing on the underlying stock prices. Through study of the links between stock market and derivative market, we argue whether the change in volatility of the underlying asset might arise from other factors rather than warrant listing across periods. The empirical results show that the introduction of equity warrant does not significantly affect the underlying asset market and the change in the volatility of the underlying stock resulted from the market-wide and industry-wide influences.

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Chapter One: Introduction

For more than one decade, China has experimented with the stock market. The Chinese stock market has been developing at a rapid rate, contributing greatly to the country's economic growth. Although the market, as an emerging market, is more volatile and less regulated than those mature markets, the Chinese stock market still draws more and more attention from the academic and the public due to the rapid economic growth of China. After the year 2000, the Chinese government introduced a series of policies with intent to develop and regulate the stock market. It is worth investigating the effects of these policies on the financial markets. Hence, this thesis examines the stability of the Chinese stock market in three perspectives as explained in the following.

In chapter two, we examine the dynamic price-volume relation on the Chinese stock market and the impact of the liquid restriction on the price-volume relation. In the literature of market microstructure, the relationship between stock returns and trading volume has been discussed for a long period because it is potentially important in understanding how information is transmitted to the market as well as is embedded in stock prices, and we can learn more if we study the joint dynamics of stock and trading volume.

In theory, there exist the linear and nonlinear causal relations between stock return and trading volume. A number of empirical studies, most of which are based on the U.S. market, supports this theoretical arguments. In chapter two, we test linear and nonlinear causal relation between price changes and trading volume both for the index and for ten active individual stocks on the Shanghai Stock Exchange, which form a substantial fraction of the portfolios of mutual fund. However, our empirical findings are inconsistent with the theoretical expectation. We find that this different price-volume relation that non-linear causal relationship is not found on the Chinese market may result from differences in regulation and information flows, as Jennings, Starks and Fellingham (1981) point out that these factors affect market behaviour.

As is known, same shares issued by the same enterprise should enjoy the same rights. This is a basic principle of a shareholding economy. But on the Chinese stock market the implementation of this principle has been seriously hampered. Two-thirds of all the shares of China's listed companies are not tradable on the secondary market. We show that the existence of the liquidity constraint does affect the price-volume relation, which causes the existence of non-linear causal relation not found before the constraint is relaxed.

In chapter three, we investigate the impact of institutional investors on overall market prices. The Chinese stock markets are dominated by individual investors. In the A-share market, more than 99% of traders are individuals while in the B-share market, more than 93% are individual traders[1]. Individual investors tend to follow the market in their trading and exhibit apparent herd behaviours. It is highly necessary to establish mutual funds, foster the growth of corporate investors that aim at the appreciation of long-term capital and provide guidance to market investment activities. Hence, the government implements the policy to launch a number of mutual funds, which attract millions of investors to shift low-interest bank deposits into the stock markets. In the view of the growing influence that investment funds exert on the structure of capital markets, it is worth taking a closer look at the functioning of these investors.

In literature, the impact of institutional investors is not yet conclusive. Efficient market theory suggests that institutional investors arbitrage irrationalities in individual investors' responses to information, and provide a stabilizing influences on stock prices. However, if there exists the positive feedback trading or herding, these trading behaviour may drive asset prices away from fundamental values and result in destabilizing impact on stock prices. In chapter three we study the fund flow-volatility relation at the aggregate level and provide empirical evidence of the impact of institutional investors on market prices. It is the first time in the literature using aggregate data, the fund index, to investigate this issue. In general, our results show that mutual fund trading contributes to the market-wide volatility, and their trading stabilizes market prices on the Shanghai Stock Exchange. The absence of herding

[1] Source: The Chinese Securities and Futures Statistical Year Book, 2001.

formation generated by fund investors at the aggregate level does not support the hypothesis that investment fund's trading destabilizes stock prices.

In chapter four, we explore the impact of warrant listing on the underlying stock. This is the first study on Chinese equity derivative markets. As discussed above, two-thirds of shares are not tradable on the secondary market, which affects market behaviour. In 2005, China's securities regulator allows the nation's publicly traded companies to give shares, stock options and warrants to directors, senior managers and other employees. It seems that the government wants to support its pilot program to dispose of nontradable shares through the issue of warrants. After 1995[2] the first warrant was listed on Shanghai Stock Exchange on 22nd August 2005.

Stock options and warrants are rights to buy a certain number of shares at a specific price during a set time period. Warrants are stock option-like derivatives that are issued by firms to attract retail investors, who are interested in taking leveraged bets, through lower transaction costs. In a complete market, theoretically with no transaction costs and trading constraints, a stock option is regarded as a redundant security, since its pay offs can be synthesized by combining a position in the underlying stock with risk-free lending and borrowing. However, in the real world, where dynamic trading strategies replicating option payoffs are infinitely costly, introducing options may have an impact on the underlying asset stock prices and their variances. Options provide an opportunity for market makers to hedge their exposure, allowing them to lower the bid-ask spread. The availability of options as hedging vehicles makes investment in riskier stocks more attractive and this leads to increase the demand for the underlying asset because they need to hold a certain amount of the underlying asset for delta hedge. Consequently, with their ability to improve liquidity, options should stabilize the underlying stock market. Nevertheless, if derivatives have a destabilizing impact on the financial market, this would be a particular concern for market regulators and those companies with derivatives written upon them. In addition, implied volatility contains useful information in forecasting volatility for that option implied volatility provide market information about the expected return volatility of the underlying asset for the period until the expiry date of the contact.

[2] A limited number of companies were allowed to issue warrants before 1995. However, warrant trading led to excessive speculation in 1995. After that, warrants were banned.

In literature, most empirical research is usually conducted to measure the impact of the introduction of option or futures on the underlying asset in the developed market and the debates are still open. Chapter Four contributes to the knowledge of the impact from derivative asset on underlying assets as it is among very few studies that investigate the impact from warrant listing in emerging market. Being different from previous research, we employ the GARCH model with cross-sectional market-wide and industry-wide volatility to explore whether or not there is a permanent change in the volatility of the underlying asset after warrant introduction. We find that after controlling for market level and industry level influences, the introduction of warrant has no significant effect on the volatility of the underlying stock. Moreover, the implied volatility of warrant is informative but it does not subsume the information contained in all other variables in the market information set.

Chapter Two: Nontradable shares matter in the Chinese Stock market – Testing the dynamic price-volume relation

1. Introduction

The relation between stock returns and trading volume has gained much attention from both academics and practitioners in the financial community because it is potentially important in understanding how information is transmitted to the market as well as embedded in stock prices. A considerable body of literature has attempted to document the empirical and theoretical nature of this relation with divergent results. The significance of this study may be realized from the assertion put forward by Karpoff (1987) that emphasizes the price-volume relation's implications for financial markets. Gallant, Rossi and Tauchen (1992) point out that more can be learnt about the stock market by studying the joint dynamics of stock prices and volume than by focusing only on the univariate dynamics of stock prices. Studying the joint dynamic models provide a good understanding of stock price movements, which has significant implications for asset pricing models, regulators, hedgers, speculators and other participants on financial markets. Furthermore, the stock price-volume relation can be used as the basis for a trading strategy, and as evidence for or against the efficiency of stock markets.

Hiemstra and Jones (1994) test linear and nonlinear Granger Causality in the stock price-volume relation. Meanwhile, they give the summary of the explanations for a causal price-volume relation. The sequential information arrival model provides the first explanation.[3] Due to the sequential informational flow, lagged trading volume could have predictive power for current absolute stock returns, and lagged absolute returns could have predictive power for current trading volume. Tax and non-tax-related motives for trading are a second explanation. Lakonishok and Smidt (1989) conclude that current volume can be related to past stock price changes due to tax- and non-tax-related trading motives. The mixture of distribution models by Clark

[3] See Jennings, Starks and Fellingham (1981).

(1973) and Epps and Epps (1976) is the third explanation for the price-volume relation.[4] The noise trader model given by Delong, Shleifer, Summers and Waldmann (1990) provides a fourth explanation. Due to the assumption that trading strategies pursued by noise traders cause stock prices to move, trading volume causes the stock price to change and the quantities have a positive relation. On the other hand, there exists a positive causal relation from stock returns to volume in terms of the positive-feedback trading strategies of noise traders. Furthermore, Fama (1965) points out that irrational investors are met on the market by rational arbitrageurs who trade against them and in the process drive price close to fundamental values. In the course of such trading, those whose judgments of asset values are sufficiently mistaken to affect prices lose money to arbitrageurs and so eventually disappear from the market. Hence, understanding the nature of the returns and trading volume relation on the market has important implications in valuing portfolio returns and investment decisions, and should be useful to regulators and participators, too.

Although there has been extensive research into the empirical and theoretic aspects of the price-volume relation, a lot of work has been focusing on the developed financial markets, for instance, the U.S. market, but just a little work has been done on the emerging markets of developing countries. While, there are many differences from developed markets to emerging markets, such as markets size, regulation, information flows and so on. This chapter investigate the behaviour and the price-volume relation on the Chinese market. We try to find out the fact whether or not there is the existence of different characteristics between developing market and developed market.

Partially attributed to the lack of reliable and consistent data, little work has been conducted on the Chinese stock market. Moreover, most of the existing works employ share-price index data rather than data for individual stocks to examine the price-volume relation. However, Wang (1994) shows that heterogeneity among investors gives rise to different volume behaviour and price-volume dynamics. Hence, this paper extends the existing literature in several ways.

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[4] There is existence of a positive causal relation running from trading volume to absolute stock returns in Epps and Epps (1976). While, true causal relation from trading volume to stock returns has not been found in Clark's common-factor model.

Firstly, we investigate the dynamic relation between price and volume for both of A-Share Price Index and ten large and active individual stocks listed on Shanghai stock exchange for the period January 2002 to September 2003[5]. Because mutual funds have to disclose their portfolio quarterly[6] and mention the stocks that form a substantial fraction of the portfolios of mutual funds, the first ten stocks are chosen according to their ranking by the number of times they are mentioned during the seven quarters in our sample. A-share price index is chosen as benchmark compared with individual stocks.

Secondly, we employ the method, suggested by Baek and Brock (1992), and Hiemstra and Jones (1994), to investigate the linear and nonlinear causal relation between stock returns and trading volume with and without the liquid constraint. Chinese financial market as an emerging market has some special regulations. Regarding most public companies in China, there are two thirds of shares that can not be traded freely on the secondary market. Typically these shares belong to the State or to domestic financial institutions ultimately owned by central or local governments. Our findings show that this liquidity constraint results in different information flow and affects the price-volume relation.

This paper proceeds as follows. In Section 2, we provide a briefly review of the previous research on the relation between price changes and volume. In Section 3, we discuss the methodology used in this paper. In Section 4 and 5, we describe the data and the preliminary analysis, and present the empirical results, respectively. Section 6 shows the impact of illiquidity on the price-volume relation. Finally, in Section 7 we provide conclusion and summary.

[5] The sample period for A-Share Price Index is extended to December 2006.

[6] In China because mutual funds are listed and traded on the securities market, they have to meet the information disclosure requirements on securities. The requirement on listing documents and public announcement, the publication of the fund's net capital and the semi-annual and annual reports are similar to that of a listed stock. Furthermore, they have to disclose their holdings of stocks quarterly.

2. Literature review

The relation between price change and trading volume is potentially important in understanding how information is transmitted to the market as well as embedded in stock prices so researchers concentrate on this field and a number of theoretic work and empirical studies has been done. This section presents a brief review of these issues.

2.1 The importance of volume

In standard rational expectations models with aggregate supply uncertainty, volume plays the role of adding noise to the model. Allowing traders to observe volume essentially allows them to know the aggregate supply, and this results in a fully revealing single price. In this framework, the information role of volume is large, but vacuous. With no role to play other than noise, volume in these models can never provide insights into underlying economic fundamentals or guidance to the process by which information is impounded into the price. However, in fact volume plays an important role on the market.

Campbell, Grossman and Wang (1993) detect a relation between trading volume and the serial correlation in stock returns. Public information arrival and exogenous pressure by noninformational traders are two causes of price change. If public information has arrived, there is no reason to expect a high volume of trade, whereas pressure by noninformational traders must reveal itself in unusual volume. They conclude that the first-order daily return autocorrelation tends to decline with volume. It means that price changes accompanied by high volume will tend to be reversed, and that this reversal will be less true of price changes on days with low volume. In their paper, volume is interesting for its correlation with other variables, and traders never learn from volume nor use volume in any decision making.

Blume, Easley and O'Hara (1994) develop an alternative equilibrium approach for studying the behaviour of security markets entering learning problems because traders use the specific volume statistic in upgrading their beliefs. The model is standard in that some fundamental is unknown to all traders and traders receive signals that are informative of the asset fundamental. However, they use an additional assumption that aggregate supply is fixed. The source of noise is the quality of the information, specifically the precision of the signal distribution. Price, which they assert, cannot provide full information on both the magnitude of the signals and precision. They show that volume provides information about the quality of trader's information that cannot be deduced from the price process. The technical analysis based on their paper arises as a natural component of the agent's learning process - A trader observing only a high price is unable to determine whether the price is high because of a high average signal or an average signal with a high quality. Thus, the role of volume now becomes apparent why observing price and volume together is more informative than observing price alone. It as a signal of the precision of beliefs means that the volume statistic provides information to the market that is not conveyed by the price.

Moreover, this information is related to information about the asset value and not to exogenous liquidity or supply shocks. Pring (1991) shows the same picture as Blume, Easley and O'Hara (1994). In the model, the independence of volume is also what allows the quality of information to be inferred from the market statistics. Therefore, it becomes natural to watch volume because it complements the information provided by price. A trader watching only prices cannot learn as much as a trader watching both prices and volume and so faces an unnecessary penalty if he ignores the volume statistics.

Wang (1994) develops an equilibrium model of stock trading in which investors are heterogeneous in their information and private investment opportunities. Investors trade rationally for both informational and non-informational reasons. Wang (1994) uses the model to study the behaviour of stock trading volume and its relation with returns. His model shows that heterogeneity among investors gives rise to different volume behaviour and price-volume dynamics. In his model trading is always accompanied by price changes and trading volume is always positively correlated with price changes. On one hand, under symmetric information if the stock price changes for public news about the stock's future dividends, there is no trading accompanying the price change and the expected excess return on the stock remains the same since the new expectation of future dividends is immediately reflected in the price. While if the price changes for investor's private investment opportunities, there is trading accompanying the price change and the expected future returns changes since informed investors try to rebalance their portfolios and attract the uninformed investors to trade. On the other hand, under asymmetric information, if the uninformed investors' trade for correcting the errors made in previous trading when new information reveals the stock's true value, a high volume accompanied by a low return implies a low return in the future. Nonetheless, if the reason of uninformed investors' trading is to take new positions when price adjusts to reflect the need of non-informational trading from the informed investors, a high volume accompanied by a low return implies a high return in the future. This implies that trading volume conveys important information about how assets are priced on the market and the dynamic price-volume relation can reveal the natural of investor heterogeneity. Consequently, in the general case of the model he points out that the whole history of returns and volume can be used to predict future returns and there exists the nonlinear relation between stock return and trading volume. It is a further step to Campbell, Grossman and Wang (1993)'s conclusion.

Llorente et al. (2002) allows us to get sharper predictions on the dependence of a stock's dynamic volume-return relation on the extent of information asymmetry. They find significant differences in the dynamics of returns and volume across stocks with different degrees of information asymmetry. Stocks of smaller firms or stocks with higher bid-ask spreads have a tendency for return continuation following high-volume days. While stocks of large firms or stocks with smaller bid-ask spreads show almost no continuation and mostly return reversal following high-volume days. Their work is consistent with the research by Wang (1994) that the difference in information and investment opportunities results in different price-volume dynamics.

Moreover, He and Wang (1995) develop a multi-period rational expectations model of stock trading in which investors have different information concerning the underlying value of the stock. In their model, investors' informational trading depends on the expected gains from speculation and the risk involved. As investors continue to trade, more private information is revealed through prices and the expected gains from speculation decrease. The risk associated with speculation depends on the uncertainty in the stock's future payoff and the trading opportunities remaining before the uncertainty is fully resolved. Hence, the tradeoff between two factors determines investors' dynamic strategies. He and Wang (1995) find that the pattern of volume is closely related to the flow and nature of information over time, meanwhile, equilibrium prices are noisy and do not fully reveal all the investors' information. Their results show that volume may lag behind the information flow when the information is private. The current volume is not only related to the contemporaneous information, but also related to existing private information received previously. Volume generated by new information, private or public, is accompanied by significant price changes, while volume generated by existing information is not.

2.2 The causality between the stock price and trading volume

To find such causal relations provides information on whether knowledge of past movements in trading volume improves short-run forecasts of current and future stock prices movements or vice versa. Previous studies on the stock price-volume relation have used tests that rely on the restrictive assumption of linearity.

In empirical studies, Karpoff (1987) offers a detailed survey of the early literature on relation between the stock price and volume. Smirlock and Starks (1985, 1988) find that the price-volume relation is asymmetric and a strong positive lagged relation between volume and absolute price changes using individual stock data. De Jong, Nijman and Roell (1996) allow prices to depend linearly on trading volume and measure the impact of trades on transaction prices. Moreover, Chen, Firth and Rui (2001) check the relation between daily market price index and trading volumes. They use the data set covering nine of the largest stock exchanges that are large, well established and well regulated. They find the strong evidence for the causal relation from returns to volume in all nine markets, while the causal relation from volume to returns is detected just in four markets. Hence it implies stronger evidence of returns causing volume than volume causing returns.

Saatciolgu and Starks (1998) use monthly data to examine the stock price and volume relation in six Latin America emerging markets, and discover a positive relation between volume and price changes. They also provide evidence that stock price changes do not lead volume, but volume leads stock price changes. This finding is contrary to many studies based on U.S. data. Ratner and Leal (2001) examine the statistical relation between stock returns and trading volume on the emerging markets of Latin America and Asia. They confirm that there is existence of bi-directional

Granger-causality between these two variables. However, volume's ability to Granger-cause stock returns is significantly enhanced when a contemporaneous independent variable is introduced. Their findings contradict the results provided by Saatciolgu and Starks (1998).

Although the majority of models for prices are linear with trading volume, several empirical studies investigate the existence of nonlinearities. Hiemstra and Jones (1993) argue that the traditional Granger causality test that is designed to detect linear causality is ineffective in uncovering nonlinear causal relation. Their research provides the support to the argument by Gallant, Rossi and Tauchen (1992). In Hiemstra and Jones following paper in 1994, they investigate the linear and nonlinear causal relations between the stocks price and trading volume modifying the Beak and Brock (1992)'s nonparametric model to examine the dynamic relation between those two variables.

Moreover, De Jong, Nijman and Roell (1995) find that transaction prices are affected by trading volume in a nonlinear way by exploiting the data of French stocks traded on the Paris Bourse and SEAQ International. And Kempf and Korn (1999) establish a nonlinear, concave relation between trading volume and prices of German futures, using neural networks. Dridi and Germain (2000) model a financial market where informed traders receive a signal that perfectly reveals the sign of the difference between the liquidation value of the asset and its true value, but not the exact value. This type of information is called bullish or bearish. They show that the assumption of bullish and bearish information has a large impact on prices. And they find that the optimal trading strategies in equilibrium are not linear and that, consequently, the impact function is a nonlinear function of trading volume.

3. Methodology

In order to examine the dynamic relation between stock prices and trading volume on the Chinese stock market, we employ the linear and nonlinear Granger Causality tests to shed lights on it. So in the first half of this section, we briefly discuss the linear Granger Causality because this approach is well known in literature. In the remainder of this section, we introduce a detailed discussion of new approach following Baek and Brock (1992), which can be used to test for nonlinear Granger causality.

3.1 Linear Granger Causality Tests

3.1.1 Definition

Granger (1969) develops an approach, which is called Granger causality, to test the causal relation between two scalar-valued, stationary, and ergodic time series. Let $\{X_t\}$ and $\{Y_t\}$ be two time series that satisfy the assumptions given by Granger (1969). Let $F(X_t|\Phi_{t-1})$ be the conditional probability distribution of X_t given the information set Φ_{t-1}, which is $\Phi_{t-1}=\left\{X_{t-Lx}^{Lx},Y_{t-Ly}^{Ly}\right\}$. X_{t-Lx}^{Lx} and Y_{t-Ly}^{Ly} indicate a Lx-length lagged vector of X_t and a Ly-length lagged vector of Y_t, $X_{t-Lx}^{Lx}=(X_{t-Lx},X_{t-Lx+1},...,X_{t-1})$ and $Y_{t-Ly}^{Ly}=(Y_{t-Ly},Y_{t-Ly+1},...,Y_{t-1})$, respectively. Given lags Lx and Ly, the time series $\{Y_t\}$ does not strictly Granger cause $\{X_t\}$ if

$$F(X_t|\Phi_{t-1})=F\left[X_t\middle|\left(\Phi_{t-1}-Y_{t-Ly}^{Ly}\right)\right],t=1,2,3,... \qquad (2.1)$$

The hypothesis of interest states that taking the vector of past Y values out of the information set does not affect the distribution of X values[7]. If the equality in equation (2.1) does not hold, then knowledge of past Y values helps to predict current and future X values, and we say that Y strictly Granger causes X. Similarly, if

$$F(X_t|\Phi_{t-1})=F\left[X_t\middle|\left(\Phi_{t-1}+Y_t\right)\right],t=1,2,3,... \quad (2.2)$$

[7] Granger Causality typically refers to the conditional expectation.

there exists a lack of instantaneous causality from Y to X. On the other hand, if the equality in equation (2.2) does not hold, where the current value of Y is added into the information set, and then Y is said to instantaneously Granger cause X. In this chapter, we concentrate on testing for strict Granger causality alone due to problems with distinguishing between instantaneous causality and instantaneous feedback.[8]

3.1.2 Testing Causality

To test linear Granger Causality, consider the two following equations:

$$X_t = \sum_{i=1}^{m} \alpha_i X_{t-i} + \sum_{i=1}^{n} \beta_i Y_{t-i} + U_{X,t} \ , \ t = 1,2,3..., \quad (2.3)$$

$$Y_t = \sum_{i=1}^{r} \delta_i X_{t-i} + \sum_{i=1}^{s} \theta_i Y_{t-i} + U_{Y,t} , \ t = 1,2,3...,. \quad (2.4)$$

In above two regression models, X and Y are two stationary variables. m, n, r and s indicate the lag-lengths of the variable X and Y in both expressions, respectively. $U_{X,t}$ and $U_{Y,t}$ are the error terms with zero mean and constant variance.

Testing for the null hypothesis that Y does not strictly cause X using Granger causality is equivalent to test $H_0 : \beta_1 = \beta_2 = ... = \beta_n = 0$ against H_1 : at least one $\beta_i \neq 0$ using the standard joint F or χ^2 test. If the coefficients of β_i ($i = 1,2,3,...n$,) in equation (2.3) are jointly significantly different from zero, the null is rejected and lagged Y has significant linear predictive power for current X. At the same time, if the null that all δ_i s are equal to zero is rejected in equation (2.4) as well, that means X strictly Granger causality Y. When both of the null hypothesizes are rejected, it means the existence of bi-directional causality between the two variables. In the bivariate case, the presence of Granger causality is tested by evaluating the predictive power of one time series for another.

[8] Geweke, Meese and Dent (1983) discuss Granger causality testing procedures and some issues relating to measurement errors and distinguishing between instantaneous causality and instantaneous feedback, etc.

In order to implement this test, we have to determine appropriate lag lengths for each variable in each equation. Hiemstra and Jones (1994) use Akaike Information Criterion (1974) to choose the optimal lag lengths. In this chapter, however, we follow the sequential procedure suggested by Hsiao (1981). This approach which combines FPE[9] (Final prediction error) criterion by Akaike (1969) and Granger (1969) definition of causality allows a variable to depend on a subset of the variables under consideration and allows each variable to enter the equation with a different numbers of lags. The sequential procedure is described as following[10]:

(1) Treat X as a one-dimensional autoregressive process in equation (2.3) and compute its FPE with m varying from 1 to L that is a priori (specified) highest possible order. Choose the m that gives the smallest FPE. And the corresponding FPE is labelled FPE (m, 0).

(2) Assume X as a controlled variable with m lag length determined in step (1) and treat Y as a manipulated variable that controls for the outcome of X in equation (2.3). Compute again the FPE of equation (2.3) by varying the order of lags of Y, n, from 1 to L and determine n that gives the minimum FPE. The corresponding FPE is called FPE (m, n).

(3) Compare the smallest FPEs of the above two steps. If the former is greater than the latter, then it can be concluded that Y causes X and it means that the optimal model for predicting X is one including m lagged X and n lagged Y.

Similarly, repeat the above 3 steps to determine whether X causes Y. In that case Y is a controlled variable and X is treated as a manipulated variable in equation (2.4).

3.2 Nonlinear Granger Causality

One important problem with the linear approach to causality testing is that such tests can have low power detecting certain kinds of nonlinear causal relations. Baek and Brock (1992) propose a nonparametric statistical method for detecting nonlinear causal relations between two time series that is called nonlinear Granger causality. Their approach uses the correlation integral as an estimator of spatial probabilities

[9] The Final Prediction Error (FPE) is defined as the (asymptotic) mean square prediction error. Akaike (1969) suggests that the minimum FPE can be used to determine the order of a univariate stationary autoregressive process and/or inclusion or exclusion of a variable in the model. That means that this approach can be employed to determine the optimal lag length of an autoregressive process since it balances the risk due to the bias when a lower order is selected and the risk due to the increase in variance when a higher order is selected.

[10] Also Silvapulle and Choi (1999) follow this idea to detect the optimal lag length.

across time to detect nonlinear relations between time series instead of linear relations that can be detected using traditional causality test. Hiemstra and Jones (1994) relax the assumption by Baek and Brock (1992) that the time series are mutually independent and individually independent and identically distributed, and allow the time series to display weak temporal dependence. Weakly dependent processes display short-term temporal dependence, which decays at a sufficiently fast rate.

In this chapter, we follow this modified Baek-Brock approach (1992), which allows each series to display weak temporal dependence. To define nonlinear Granger causality, consider two strictly stationary and weakly dependence time series $\{X\}$ and $\{Y\}$. Define the $m-$length lead vector of X_t by X_t^m, and the $lx-$length and $ly-$length lag vectors of X_t and Y_t, respectively, by X_{t-lx}^{lx} and Y_{t-ly}^{ly}, which are indicated as following:

$$X_t^m \equiv (X_t, X_{t+1}, \ldots, X_{t+m-1}),\ m = 1,2,3,\ldots,\ \ t = 1,2,3,\ldots,\ (2.5)$$

$$X_{t-lx}^{lx} \equiv (X_{t-lx}, X_{t-lx+1}, \ldots, X_{t-1}),\ lx = 1,2,3,\ldots,\ \ t = lx+1, lx+2, lx+3,\ldots,\ (2.6)$$

$$Y_{t-ly}^{ly} = (Y_{t-ly}, Y_{t-ly+1}, \ldots, Y_{t-1}),\ ly = 1,2,3,\ldots,\ \ t = ly+1, ly+2, ly+3,\ldots,\ (2.7)$$

The definition of Nonlinear Grange non-causality is given by the following expression: for given values of $m, lx, ly \geq 1$, and for $e \succ 0$,

$$\begin{aligned} &\Pr(\| X_t^m - X_s^m \| \prec e \,\big|\, \| X_{t-lx}^{lx} - X_{s-lx}^{lx} \| \prec e, \| Y_{t-ly}^{ly} - Y_{s-ly}^{ly} \| \prec e) \\ &= \Pr(\| X_t^m - X_s^m \| \prec e \,\big|\, \| X_{t-lx}^{lx} - X_{s-lx}^{lx} \| \prec e), \end{aligned} \qquad (2.8)[11]$$

where $\Pr\{\cdot\}$ is probability and $\|\cdot\|$ is the maximum norm. The probability on the left hand side of equation (2.8) can be interpreted as the conditional probability that any

[11] Hong, Liu and Wang (2006) investigate the Granger Causality in risk, which is the concept of Granger Causality in variance in charactering extreme downside risk spillover between financial markets. However, in this study we only focus on the Granger Causality in the first moment, not higher moments.

two arbitrary $m-$length lead vectors of $\{X_t\}$ are within a distance e of each other, given that the corresponding $lx-$length lag vectors of $\{X_t\}$ and $ly-$length lag vectors of $\{Y_t\}$ are within e of each other. The probability on the right hand side of equation (2.8) is the conditional probability that any two $m-$length lead vectors of $\{X_t\}$ are within a distance e of each other, given that their corresponding $lx-$length lag vectors are within a distance e of each other. If the equation (2.8) is hold, then $\{Y_t\}$ does not strictly nonlinear Grange causality $\{X_t\}$. Note that although the definition concerns conditional distributions given an infinite number of past observations, in practice tests are usually confined to finite orders in $\{X_t\}$ and $\{Y_t\}$.

In the Baek-Brock approach (1992), the conditional probabilities are expressed in terms of the corresponding ratios of joint probability. They assume that $C_1(m+lx,ly,e)/C_2(lx,ly,e)$ and $C_3(m+lx,e)/C_4(lx,e)$ denote the ratios of joint probability corresponding to the left hand side and right hand side of equation (2.8). Then, the strict Granger non-causality condition could be shown as following:

$$\frac{C_1(m+lx,ly,e)}{C_2(lx,ly,e)}=\frac{C_3(m+lx,e)}{C_4(lx,e)}, \qquad (2.9)$$

where $C_1(m+lx,ly,e)\equiv \Pr(\| X_{t-lx}^{m+lx}-X_{s-lx}^{m+lx} \|\prec e, \| Y_{t-ly}^{ly}-Y_{s-ly}^{ly} \|\prec e),$

$$C_2(lx,ly,e)\equiv \Pr(\| X_{t-lx}^{lx}-X_{s-lx}^{lx} \|\prec e, \| Y_{t-ly}^{ly}-Y_{s-ly}^{ly} \|\prec e),$$

$$C_3(m+lx,e)\equiv \Pr(\| X_{t-lx}^{m+lx}-X_{s-lx}^{m+lx} \|\prec e),$$

$$C_4(lx,e)\equiv \Pr(\| X_{t-lx}^{lx}-X_{s-lx}^{lx} \|\prec e). \qquad (2.10)$$

Hence, if the equation (2.9) is not hold, that means that Y_t strict nonlinearly causes X_t for given values of m, lx and $ly\geq 1$ and $e\succ 0$.

Correlation-integral estimators of the joint probabilities in equation (2.10) are used to test the condition in equation (2.9). For the time series realizations on X and Y, say $\{x_t\}$ and $\{y_t\}$ for $t=1,2,...,T$, let $\{x_t^m\}$, $\{x_{t-lx}^{lx}\}$ and $\{y_{t-ly}^{ly}\}$ denote the $m-$length lead and lx – length lag vectors of $\{x_t\}$ and the ly – length lag vectors of $\{y_t\}$ as defined previously. Define $I(z_1, z_2, e)$, a kernel that equals to 1 when two conformable vectors, z_1 and z_2, are within the maximum-norm distance e of each other and 0 otherwise. Correlation integral estimators of the joint probabilities in equation (2.10) can be expressed as

$$C_1(m+lx, ly, e, n) \equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-lx}^{m+lx}, x_{s-lx}^{m+lx}, e\right) I\left(y_{t-ly}^{ly}, y_{s-ly}^{ly}, e\right)$$

$$C_2(lx, ly, e, n) \equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-lx}^{lx}, x_{s-lx}^{lx}, e\right) I\left(y_{t-ly}^{ly}, y_{s-ly}^{ly}, e\right)$$

$$C_3(m+lx, e, n) \equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-lx}^{m+lx}, x_{s-lx}^{m+lx}, e\right)$$

$$C_4(lx, ly, e, n) \equiv \frac{2}{n(n-1)} \sum\sum_{t<s} I\left(x_{t-lx}^{lx}, x_{s-lx}^{lx}, e\right), \qquad (2.11)$$

$$t, s = \max(lx, ly) + 1, \ldots, T - m + 1, n = T + 1 - m - \max(lx, ly).$$

Using the joint probability estimators in equation (2.11), the strict Granger non-causality condition in (2.8) can be tested. For given values of m, lx, $ly \geq 1$ and $e \succ 0$, we could have the following expression under the assumptions mentioned previously[12],

$$\sqrt{n}\left(\frac{C_1(m+lx, ly, e, n)}{C_2(lx, ly, e, n)} - \frac{C_3(m+lx, e, n)}{C_4(lx, e, n)}\right) \sim_a N\left(0, \sigma^2(m, lx, ly, e)\right). \quad (2.12)$$

This test has very good power properties against a variety of nonlinear Granger causal and non-causal relations, and its asymptotic distribution is the same if the test is applied to the estimated residuals from a vector autoregressive model.

The traditional Granger Causality test detects linear Granger Causality between stock prices and trading volume. On the contrary, the modified nonlinear test given by Hiemstra and Jones (1994) provides evidence of significant nonlinear bi-directional Granger Causality between stock prices and trading volume. Due to these results, this

[12] For more details on the proof, see Hiemstra and Jones (1994).

nonlinear approach can be regarded as a specification tool for uncovering significant nonlinearities in the dynamic interrelations between economic variables. Hiemstra and Jones (1993) present Monte Carlo evidence suggesting that the modified test is robust to nuisance-parameter problems, and find the modified test has remarkably good finite-sample size and power properties against a variety of linear and nonlinear Granger causal and non-causal relations.

4. Data and Preliminary analysis

In this chapter, the data used are based on time series of daily individual stock returns as well as trading volume obtained from the Shanghai Stock Exchange (SSE) for the period through January 2002 to September 2003. The sample period of A-Share Price Index covers from January 2002 to December 2006.We are trying to investigate the dynamic relation between stock returns and trading volume of A-Share Price Index and the first ten large stocks that are hold by mutual funds with large proportion. Due to the regulation that mutual funds have to quarterly disclose their portfolio and mention the stocks that they hold with large proportion, the first ten stocks are chosen according to their ranking by the mentioned times of the stocks during the corresponding seven quarters. We compute stock returns from daily closing prices and the daily stock returns are continuous rates of return, and the trading volume series is daily total number of shares traded on the SSE.

Stock returns are computed as percentage log return, $100\log\left(P_t / P_{t-1}\right)$, where P_t and P_{t-1} are daily stock closing prices at t and $t-1$, respectively. We have used the augmented Dickey-Fuller test for unit root testing, and find the A-Share price index and the ten individual stock prices are non-stationary in the sample and the stock return series are stationary processes while the log of trading volume is stationary process[13], which is consistent with previous studies. For instance, Chen, Firth and Rui (2001) report strong evidence of stationarity in raw trading volume series on the Chinese stock market.

Mookerjee and Yu (1999) find that there are significant negative weekend and positive holiday effects, but there is no evidence of a January effect or early January effect on both of Shanghai and Shenzhen Stock Exchanges. Hence, in order to remove the systematic effect from the return and trading volume series, a two-step procedure is employed which is based on Gallant, Rossi and Tauchen (1992)'s approach. To implement the adjustment, two regressions have to be established

$W_t = D_t\beta + v_t$, and (2.13)

[13] The null hypothesis of the unit root test for trading volume is rejected at 99% level.

$$\log\left(v_t^2\right) = D_t\gamma + \varepsilon_t \qquad (2.14)$$

where D_t denotes a vector of daily and holiday dummy variables, β and γ are conformable parameter vectors, v_t and ε_t are error terms of the above two regressions. Here, W_t is the series to be adjusted and D_t includes the adjustment regressors. The variance equation (2.14) is used to standardize the residuals from the mean equation (2.13). Then the adjusted standardized series could be written as

$$W_t^* = \frac{\hat{v}_t}{\exp\left(D_t\hat{\gamma}/2\right)}. \qquad (2.15)$$

In this case, the series W_t is replaced by the stock returns and trading volume series. Then we could have the adjusted standardized return and trading volume series, AR_t and AV_t, respectively.

Most empirical research on the stock price-volume relation focuses on the contemporaneous relation between stock returns and trading volume. Empirical evidence shows that trading volume is positively correlated with the absolute value of contemporary price changes in Karpoff (1987)'s paper. Smirlock and Starks (1985) find a positive correlation between volume and price changes. In the literature, the linear relation between stock prices and trading volume has been discussed by Smirlock and Starks (1988), Kim et al. (1991) and De Jong et al. (1996), for instance. However, such tests have low power against nonlinear relations between these two variables.

Before testing the linear and nonlinear price-volume causal relation, we examine the contemporaneous relation between two variables running by the following three regression models. This can be regarded as a preliminary investigation of non-linearity. We have

$$AV_t = \gamma_0 + \gamma_1 AR_t + u_t \qquad (2.16)$$

$$AV_t = \gamma_0 + \gamma_1 |AR_t| + u_t \quad (2.17)$$

$$AV_t = \gamma_0 + \gamma_1 AR_t^+ + \gamma_2 AR_t^- + u_t \quad (2.18)$$

where $AR_t^+ = AR_t$ if $AR_t \succ 0$ and 0 otherwise, $AR_t^- = AR_t$ if $AR_t \prec 0$ and 0 otherwise. In the above regression models, AV_t and AR_t present the adjusted standardized trading volume and adjusted standardized stock return, u_t is an error term with zero mean and constant variance. Table 2.1 and 2.2 show the results of these regressions. Equation (2.16) and (2.17) are displayed in panel A and B in Table1, respectively. In panel A, most of the slope coefficients are statistically significantly positive at 90% or 99% level except SH CONTAINER but the estimated intercepts are not significant. It means that there is a positive relation between volume and stock returns. In panel B, the similar result could be obtained that there is a positive relation between volume and absolute returns.

Equation (2.18) tests the asymmetry response on positive or negative changes in stock returns related to volume. From table 2.2, all of the coefficients are significant except γ_2 s of HAIXIN GROUP and HUANENG POWER. Any change in returns positively affects trading volume. However, the response of trading volume to a positive price change is stronger than that to a negative change. Blume, Easley and O'Hara (1994) suggest that there is an unrestricted V-shaped relation between volume and return. While, it should be an asymmetric V-shaped relation on the Chinese market in terms of our empirical finding. Also, Marsh and Wagner (2003) examine the price-volume relation under market stress using extreme model. They find the dependence is weak with asymmetry under market stress in European and Asian markets. Figure 2.1[14] provides plots of price-volume for index and ten individual stocks. There is evidence of non-linearity in the contemporaneous relation between return and volume. Overall, the analysis above is the preliminary investigation of return-volume relation.

[14] The outliers indicate that the firms experience a large shock, such as unexpected announcement by the board and policy announcement by government so that the price-volume relation is out of normal range.

5. Results

5.1 Linear causality

To detect the linear Granger causality between stock returns and trading volume series, we estimate the linear models specified in equation (2.3) and (2.4) with adjusted standardized returns and trading volume. The regression models can be written as following:

$$AR_t = \sum_{i=1}^{m} \alpha_i AR_{t-i} + \sum_{i=1}^{n} \beta_i AV_{t-i} + U_{AR,t}, \; t = 1,2,3..., \quad (2.19)$$

$$AV_t = \sum_{i=1}^{r} \delta_i AR_{t-i} + \sum_{i=1}^{s} \theta_i AV_{t-i} + U_{AV,t}, \; t = 1,2,3...,. \quad (2.20)$$

Table 2.3 exhibits the results of using Hsiao procedure for testing causality[15]. There is strong evidence that stock return causes trading volume not only at the index level but also in ten individual stocks that are held with large proportion by mutual funds. It implies that stock return series has strong linear predictive power for trading volume series. Strong evidence that trading volume series causes stock return can just be found in A-SHARE PRICE INDEX, and six individual stocks (HUANENG POWER, SINOTRANS DEV, HAIXIN GROUP, SINOPEC CORP, SHENERGY CO, and SHANGHAI AUTO). Then it represents that there is the presence of a bi-directional causal relation between price variability and volume in index and six of ten large stocks. While, the evidence of volume causing returns cannot be found in other four individual stocks. These results are also supported by the use of F-statistics.

In Clark's (1973) latent common-factor model volume serves as a proxy for daily information flow in the stochastic process generates price changes. One interpretation of the finding that the evidence of volume causing returns is not detected in four individual stocks is that volume is not a proxy for information. This is consistent with the interpretation by Blume, Easley, and O'Hara (1994) that volume provides information about the quality of information signals rather than representing the information itself. The empirical results above are consistent with the context of Chinese stock markets. On the market insider dealing is widespread and acknowledged on all sides. For instance, initially the trading generated by informed

[15] We have the similar results if we use AIC or BIC to determine appropriate lag lengths for the lag polynomials.

traders increases the trading volume and causes the movement in stock price. Then, the uninformed individual investors will respond to the price change when they observe this kind of information released by informed trading. Finally the uninformed trader's response in the next few days will cause the large trading volume and further price change[16].

Our results are similar with the findings by Long, Payne and Feng (1999). They use index data for both A- and B- shares traded on the Shanghai market for the period February 1992 to January 1994 to investigate the price-volume relation. They detect a strong contemporaneous relation between price change and volume for both A- and B- shares, which is stronger than that usually found on the U.S. market. However, they only find weak evidence of causality in either direction on the basis of Granger causality test compared with our findings.

5.2 Nonlinear causality

Baek and Brock (1992) point out that any remaining incremental predictive power of one residual series for another can be considered nonlinear predictive power if we remove linear predictive power. As the issue of concern here is the nonlinear relation beyond linearity, we need to know the linear structure of the variables before applying the nonlinear test. As suggested by Baek and Brock (1992) and Hiemstra and Jones (1994), we shall extract the residuals from linear models, which contain the variables under consideration. Moreover, the test requires the residuals to be stationary. In this study, equation (2.19) and (2.20) are estimated to remove the linear predictive power of one series for another and the residuals of these models are employed to do the nonlinear causality test.

To detect the nonlinear relation using the modified Baek-Brock test, we have to choose the particular values for the lead length m, the lag lengths Lx and Ly, and the scale parameter *e*. On the basis of the Monte Carlo results in Hiemstra and Jones (1993), for all cases, they set the lead length at $m = 1$, and $lx = ly$, using common lag lengths of 1 to 8 lags. However, in this study just 5 lags are involved due to the use of daily data. In addition, for all cases, the test is applied to standardized series using a

[16] Xu (2000) points that front running by some large investors may be severe in China. Copeland and Zhang (2003) mention that the price increasing would more easily stimulate trade by ordinary investors than the price decreasing .

common scale parameter of $e = 1.5\sigma$, where $\sigma = 1$ denotes the standard deviation of the standardized time series.

Table 2.4 shows the results of the modified Baek and Brock test applied to the estimated residuals, $U_{AR,t}$ and $U_{AV,t}$ corresponding to stock returns and trading volume changes in equation (2.19) and (2.20). The evidence[17] for the nonlinear causal relation running from volume to stock returns could be found in three individual stocks (Baoshan Steel, SH Container, Haixin Group). And the existence of the nonlinear causal relation from returns to volume detected for A- share price index, and two individual stocks (Baoshan Steel and Haixin Group). This means that the evidence of bi-directional nonlinear causal relation between price variability and volume can not be obtained in A- share price index and most of the individual stocks used on the Shanghai Stock Exchange. The bi-direction nonlinear causal relation is found for Baoshan Steel and Haixin Group only. Although there is the evidence for the asymmetry pattern of contemporaneous relation between return and volume in the preliminary analysis, we can not find the evidence of nonlinear causal relation after linear causal relation removed. Apparently, these results contradict the theoretical model in which there exists the nonlinear relation between price changes and trading volume and are different from previous empirical studies based on developed markets, e.g. Hiemstra and Jones (1994). Moreover, De Jong, Nijman and Roell (1995) use data on French stocks traded on the Paris Bourse and SEAQ International and find that transaction prices are affected by trading volume in a nonlinear way. And Kempf and Korn (1999) establish a nonlinear, concave relation between trading volume and prices of German futures, using neural networks.

Overall, our empirical results show that the evidence of the linear causal relation between price changes and trading volume can be detected, and there is no evidence of the nonlinear causal relation. On the Chinese stock markets, the lack of nonlinear causal relation is not in line with the theoretical prediction. While in Jennings et. al.

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[17] Hiemstra and Jones (1994) argue that the series Y_t has the predictive power on the series X_t if the t-statistics is significant positive, and Y_t confounds the prediction of X_t if it is negative. Hence, they suggest using the right-tailed test when testing the existence of Granger causality.

(1981)'s[18] paper, they develop a theoretical model that hypothesizes a stock price-volume relation based on information flows and the existence of market institutions concluding that the price-volume relation might be different due to the information flow and market institution. This conjecture has been confirmed by Hausman, Lo and McKinlay (1992)[19]. In the next section we discover the reason why the nonlinear causal relation doesn't exist on the Chinese market.

[18] The model starts from an equilibrium situation in which all investors are satisfied with their portfolio holdings. When single information is released in the market, only one investor at that time is allowed to receive it. Based on the available information, the single participant alters his belief concerning the expected value of the distribution for the end-of-period price of the risky security. In terms of this alteration, the newly informed investor is allowed to rebalance his portfolio until the market achieves a new equilibrium so that the investor is satisfied with his portfolio position. Hence, after the sequence of events is repeated for each trader in the market, the markets reach the final equilibrium. They show that the relationship is shown to be sensitive to the number of investors, the degree of information dissemination, differences in interpretation of information and the implicit cost of the margin requirement.

[19] They use a Box –Cox transformation of trading volume as explanatory variable in an ordered probit analysis of discrete price changes. They apply the model to several stocks listed on the NYSE and show that the impact of trades on midprices in increasing trading volume and the relationship differs from stock to stock. Also Balduzzi, Kallal and Longin (1996) suggest that the tail-behaviour of the price-volume relation may differ from that of the overall joint distribution.

6. Impact of illiquidity on the price-volume relation

6.1 Nontradable shares and distortion in information flow

Shares on the Chinese Stock market are divided into broad categories: non-tradable and tradable. Non-tradable shares are held by the Sponsor's legal person, private placement of legal person, employees and others. Only outstanding tradable shares are bought or sold on the stock exchange. With regard to most public companies, there are two thirds of shares that can not be traded freely on the secondary market. The holders of non-tradable shares have exactly the same voting and cashflow rights assigned to the holders of tradable shares, but the shares cannot be traded publicly even if the company is listed. By the end of July 2002, the total non-tradable equity of the listed companies was 359.50 billon shares, 64.91% of the total the listed companies.[20] It results in the Chinese market being less liquid, and such ownership structure results in a thin stock market. Furthermore, it makes the domestic market more volatile and prone to market manipulation and insider trading, and it may cause the different information flows[21]. Meanwhile, the Chinese market has other different characteristics, for instance, individual investor domination and the existence of price limit[22], however, this chapter only focus on the effect of the existence of non-tradable shares on the price-volume relation. Due to the different information flow and the significant institutional difference across the markets, Jennings et al. (1981) suggest that they may have important implications on the stock price-volume relation. Hence, we check the impact of illiquid stocks on the price-volume relation[23].

6.2 Re-Test the causalities

Longstaff (2001) investigates the optimal portfolio choice with and without the liquidity constraint. In his model, the liquidity, which is different with the normal term defined in terms of bid-ask spread or transaction cost, is viewed as the situation where investor's ability to buy, or sell securities (at any price) is limited or restricted.

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[20] Data source: http://www.csrc.org.cn

[21] In fact, the Government and the regulatory authorities recognize the problems for the market caused by the existence of liquid constraint, and have tried to deal with the problem of non-tradable. Inoue (2005), and Beltratti and Bortolotti (2006) make a discussion on this issue.

[22] Wu (2001) documents that price limits on the Shanghai Stock Exchange have the significant effect on the stock market return and volatility.

[23] There are many markets with liquidity constraint e.g. small cap stocks. The bi-dirctional causality still can be detected in small NYSE stocks (Darrat, Zhong and Cheng, 2006). But we can't find the evidence of bi-directional causal relation on the Chinese stock market. The difference results from the fact that so many shares (two thirds) are nontradable and it affects the information flow.

It is quite similar with the real-word situation in which investors can only trade a limited amount of a stock. Due to institutional or regulatory reasons, some investors might face greater constraints than other investors.

In China, two thirds of shares are not tradable on the secondary market. According to the standard economic knowledge, a market clearing price should be achieved at which any amount of asset can be traded. However, in fact the investors are restricted to sell or buy these shares freely and the amount of tradable shares is limited on the market. Hence, it is quite different to reconcile with the economic theory.

In fact, the investor no longer has complete control over the fraction of wealth held in the form of the risky asset when liquidity is constrained. Longstaff (2001) argues that additional wealth needs to be given to the investors to make an investor facing trade restrictions as well of as he would be in their absence. The amount of additional wealth required can be reviewed as the shadow cost of illiquidity. In his model, the investor's optimal portfolio strategy is independent of his wealth level then increasing his wealth by a factor of η results in the investor purchasing η times as many shares of the risky asset initially. So increasing his wealth by a factor of η can be interpreted as reducing the price per share by a factor of $1/\eta$. Based on Longstaff (2001) and Kahl et al. (2003)'s work, Wu and Wang (2003) price the illiquid shares and show the cost of holding these restricted shares. The shadow price of liquidity is determined by comparing the constrained and unconstrained utilities of wealth and solving for the discount in the price of the illiquid asset that compensates the investor for the liquidity restrictions. The investor is subject to welfare loss if he has the restricted stocks. To ensure that the investor has the same utility with and without the restricted stocks, additional wealth needs to be given to the investor so it implies that it must be a discount for illiquidity. That is called "Utility Equivalence Theorem". For simplicity if the investor wants to achieve the utility that he has when he buys N_r shares of restricted stocks, the same as the one, which he gets when he buys N_u shares of unrestricted share with the price of P_u, the following condition must be satisfied:

$$N_u P_u = N_r P_r \quad (2.21)$$

That means that the investor has the same utility of either holding N_r shares of restricted stocks with the price of P_r or N_u shares of unrestricted share with the price of P_u. Hence, Wu and Wang (2003) suggest that the price of the restricted stocks could be derived in terms of the condition above[24].

We calculate the price of each individual stock involved in this study using the method mentioned above if we assume that the liquidity constraint is relaxed and there is no price jump[25], in other words, all the shares would be allowed to be traded freely on the secondary market. In the spirit of Utility Equivalence Theorem, it implies that the investors should have the same utilities with and without the restriction. So the share price after the restriction is removed is equal to the utility of the current tradable shares divided by the total number of the outstanding shares.

Next we need to re-calculator the trading volume if the constraint is removed. Firstly, we define that the turnover ratio is equal to trading volume divided by the number of tradable shares with the restriction. Secondly, we assume that the turnover ratio is the same with and without the restriction. So the trading volume of each individual stock is the product of the turnover ratio and the total outstanding shares of each individual stock after the constraint is relaxed. Then we recheck the price-volume relation using reconstructed price and trading volume after the liquidity constraint is removed.

6.3 Nonlinear causalities presence

We do the linear and nonlinear causality tests using the price and trading volume obtained after removing the liquid restriction. Firstly, we get the strong evidence of the linear price-volume relation as shown in section 5. Secondly, the significant

[24] In China all non-tradable shares can only be transferred privately or through irregular scheduled auctions. The average discount for non-tradable shares relative to their floating counterpart is 77.93% and 85.59%, respectively based on auction and private transfers (Chen and Xiong, 2001). While, Silber (1991) shows that Rule 144 letter stocks with a two-year no trading restriction have an average price discount of 35% relative to the freely traded common shares of the same company.

[25] Wu and Wang (2003) point out that those illiquid shares may be tradable unexpectedly one day and this kind of event risk is taken into account in the model, and they assume that there is no price jump when this restriction is relaxed. Beltratti and Bortolotti (2006) argue that price effects could emerge if the demand curve for stocks slopes down and the nontradable share reform were associated with a supply shock. On the other hand, improving liquidity should decrease premium and increase the stock price, and liquidity effect may be treated as an offsetting force with respect to the supply shock. Moreover, the authorities are establishing a set of plan to increase demand to prevent a future supply shock, i.e. qualified foreign institutional investors (QFII) can invest in A-shares, which currently only domestic investor can invest in.

evidences of the nonlinear causal relation between stock returns and trading volume are revealed. From table 2.5, the results show that the evidence of the nonlinear causal relation from volume to returns is got for nine individual stocks except Sinotrans Dev. And the nonlinear causal relation from returns to trading volume is obtained for six of ten stocks. Overall, six of ten stocks exhibit the significant bi-direction nonlinear causal relation between returns and volume after the liquid constraint is taken into account. Hence, these results imply that the existence of the large proportion of non-tradable shares on the Chinese stock market affects the price-volume relation. On the market the amount of shares is restricted so that the adjustment ability of trading quantity is limited and investors can not buy or sell the shares freely in terms of the information delivered from market prices. In the meantime the adjustment of stock price is restricted due to the price limit although trading volume conveys important information about how assets are priced on the market. Hence, the results are consistent with the conjecture by Jennings et al. (1981) and Wang (1994)[26] that the different information flow and the significant institutional difference across the markets may have important implications on the stock price-volume relation.

[26] Wang (1994) uses the model to study the behaviour of stock trading volume and its relation with returns. It is shown that different heterogeneity among investors gives rise to different volume behaviour and price-volume dynamics.

7. Conclusion and Summary

In literature, researchers mention that more can be learned about the stock market by studying the joint dynamics of stock prices and volume than by focusing only on the univariate dynamics of stock prices, and that the joint dynamics provide a good understanding of stock price movements. In general, volume does tell us something about future price movements. However, the actual dynamic relation between volume and returns depends on the underlying forces driving trading.

This study concentrates on investigating the dynamic relation between stock returns and trading volume on the Shanghai stock market. Compared with most previous studies, we regress volume on price changes both for the index and for ten individual stocks and find strong evidence of a positive contemporaneous relation between stock returns and trading volume. Moreover, an asymmetric V-shaped relation is contemporaneously discovered both for the index and for individual stocks. These findings are consistent with previous theoretical and empirical work. As is known, causality tests can prove useful information on whether knowledge of past stock price movements improves short-run forecasts of current and future movements in trading volume, and vice versa. Hence, in this chapter traditional Granger causality tests and a modified nonparametric approach are employed to test the linear and the nonlinear causal relations between these two variables. The results suggest the existence of the linear bi-directional causal relation both for the index and for six of ten stocks. However, there is no significant evidence to support the nonlinear causal relation between returns and trading volume except for one individual stock only, if we just use the data from the market unadjusted.

As is well-known, the Chinese market as an emerging market is more volatile than developed markets and is dominated by individual investors. Moreover, two thirds of shares are non-tradable on the secondary market, which causes the liquidity constraint against investors. Having relaxed this constraint, we obtain the significant evidence of nonlinear causal relation between returns and volume. The results show that the existence of liquidity constraint affects the price-volume relation, which confirm Jennings et al. (1981)'s conjectures. Due to differences in regulation, market size and information flow, we find some differences in empirical results compared with those from developed markets. Hence, this research sheds the light on the market behaviour of stock on the Chinese market, in particularly, on the impact of illiquidity, and show to the regulators and participants that the illiquidity caused by the non-tradable shares dampens the nonlinear causality in both directions between returns and trading volume.

Chapter Three: Do funds destabilize the Chinese stock market?

1. Introduction

Due to the increase in the number of institutional investors trading in stock markets, financial researchers are interested in exploring institutions' impacts on stock prices. A key question of interest is whether institutions destabilize or stabilize equity prices. Efficient market theories suggest that institutional investors arbitrage irrationalities in individual investors' responses to information and provide a stabilizing influences on stock prices. However, institutions herd together and follow the positive feedback strategy or trade based on past returns, which may drive asset prices away from fundamental values. These trading behaviours of institutions result in destabilizing impact on stock prices. In this chapter, we are to investigate whether or not funds destabilize the stock market in China.

In general, institutional investors are more sophisticated, managing a large fund and generating a large trading volume compared with individual investors. The microstructure literature confirms that substantial trades can have a large impact on stock prices. Gabaix et al. (2006) present a model in which volatility is caused by the trades of large institutions. They expect that large funds can move the market significantly. They show a simple case to support the idea that large funds are indeed large compared with the liquidity of the market and that the price impact will be an important consideration. In their model, large investors generate significant spikes in returns and volume. They point out that a small number of large institutional investors could cause extreme movements in stock prices without any news perceived.

The main argument is that institutional investors destabilize stock prices and increase the volatility of the market because of the presence of positive feedback trading and herding. A number of recent empirical studies have provided some evidences that institutional investors (e.g. mutual funds) have been engaged in positive feedback trading – buying when the price increases and selling when it falls. If rational speculators' early buying trigger positive feedback trading, then an increase in the number of forward-looking speculators can increase volatility around the equilibrium price implied by market fundamentals. Delong, Shleifer, Summers and Waldmann (1990) summarize a number of forms of behaviour in financial markets which could be described as positive feedback trading, and mention that positive feedback strategies are common in financial markets. These similar studies suggest that institutional investors exhibit herd behaviours.

Lakonishok et al. (1992), and Bohl and Brzeszczynski (2005) summarize the impact of institutional trading on stock prices. However, the available evidence does not necessarily imply that institutions destabilize the market[27]. If the positive feedback trading is a rational response to the market signal, institutions' behaviour will enhance the market efficiency and reduce the possibility of sudden change in the market. If so, they might move them toward rather than away from fundamental. Then such trading may contribute to stabilize prices rather than destabilize prices. Similarly, if institutions herd and response to the same fundamental information, they will speed up the adjustment of stock prices to new information and enhance the market efficiency. Then, they will stabilize stock prices instead of destabilizing them. Hence, empirical findings of institutional investors' herding and positive feedback trading behaviours are not necessarily evidence in favor of the destabilizing effect on stock prices.

As it is known, the Chinese stock market has grown rapidly during the last decade in terms of the number of listed companies and market capitalization. However, as an emerging market compared with those mature markets, it is more volatile and is dominated by individual investors. In the end of the 1990s, government set up a set of plans, and implemented a number of policies to encourage institutional investors, e.g. mutual funds, to join the market. Basically, these policies had two main aims. The first one was to crow out more investors of the banking system and into the stock market so that their capital can be more efficiently allocated. Second, the government wanted to alter the style of the market from the one dominated by short-term speculation to another one of long-term, professionally managed investment. Hence, a

[27] Lakonishok et al. (1992), Cohen et al. (2002) and Bohl and Brzeszczynski (2005) provide empirical evidences that do not support the hypothesis that institutions destabilize stock prices.

number of mutual funds were established since then, and massive amount of money was collected by mutual funds from the public.

The Fund Index was first reported on 9th June 2000 to indicate the market behaviour of all mutual funds listed on the Shanghai Stock Exchange. Before the year 2000, the majority of investors on the market were small, private investors and there were also some mutual funds active on the market but they had relatively small amount of capital under their management. After that, mutual funds became important players on the stock market and the role of fund investors on financial markets is likely to be more important. Mutual funds grow to be an important component of the assets held by households, so cash flows into different types of mutual fund could be a very good indicator of changes in investors' demand for financial securities. Then it becomes a prevailing argument for both participants and researchers whether fund trading behaviour is a stabilizing or destabilizing force on the financial markets. In this study, we explore what the impact of institutional trading causes on stock prices, and detect the relation between market volatility and mutual fund cash flows, in order to have a better understanding of mutual fund investor's behaviour – not only of their reaction to past market performance, but also of their attitude to investment risk.

Our contributions in this research are: 1) to extend the research of institutional trading behaviour to the Chinese market; 2) to provide the direct evidence of the impact of institutional trading upon stock prices; and 3) to examine the relation between market volatility and fund flows using high frequency data at the aggregate level. The existing literature on institutional trading is predominantly based on institutional ownership data to infer the behaviour of institutional investors[28], or use low frequency data, e.g. monthly and quarterly data, to examine the relation between fund flows and stock returns by using OLS. Hence, previous research provides only indirect empirical evidence on the destabilizing effects of institutional investors' trading behaviour on stock prices. This chapter extends this analysis to the Chinese market and contributes to the literature on this field by using aggregate daily data and providing the direct evidence. We exploit Shanghai A-Share Price Index and the Fund Index to investigate the impact of institutional trading and the relation between market

[28] See Nofsinger and Sias (1999), Dennis and Strickland (2002), and Faugere and Shawky (2003).

volatility and fund flows using daily data because the daily frequency of the data allows for more efficient estimates of time variation in systemic risk than lower frequency data does. Furthermore, we construct GARCH models to address the impact of institutional trading and the relation between volatility and fund flows rather than OLS approach used in the previous literature. We find out that the market volatility is reduced after the mutual funds played important role on the market, and the aggregate fund flows are positively correlated with subsequent market returns and negatively correlated with subsequent conditional market volatility. All these are the direct evidences of fund trading stabilizing the stock market. Finally, we show that the herding formation can not be detected on the market. It supports our empirical results that trading generated by mutual funds does not destabilize markets prices.

This chapter is organized as follows. We give a brief summary of the related literature in section 2. In section 3, we describe the data sets used for this study. We introduce the methodologies adopted to examine the impact of fund trading on stock price in section 4. The empirical findings are shown in section 5. And section 6 discusses whether there is the presence of herding formation. Finally, section 7 summaries our findings.

2. Literature Review

2.1 A mixture view of trading process and price effect

Researchers have long studied the equity trading process and its impact on stock prices. Much prior empirical research isolates individual trades and analyzes the behaviour of the stock price around each trade. They consider an individual trade as the basic unit of analysis in the study of trading activity and its effects on prices. However, institutional investors generate large block trading and an investment manager's order is often broken up into several trades. Hence, researchers try to answer the question what is the effect of institutional trading on stock prices. Demand and supply theory provides the theoretical support for the relation between fund cash flow and price return. The changes in demand for stock represented by fund cash flows drive the market price to the new equilibrium. Changes in fund cash flows reflect the shift in investors' demand for assets and they are a potential factor in determining the market movement. Chan and Lakonishok (1995), for instance, use the record of trades executed by 37 large investment management firms to study the price impact and execution cost of the entire sequence of trades. They also examine the behaviour of stock prices immediately before and after trade packages. Their findings are consistent with previous research, which has documented that large block trades have a substantial price impact[29]. Sias and Starks (1997) study in the relation between serial correlation in daily return and the institutional trading. They conclude that institutional trading reflects information and increases the speed of price adjustment, and institutional investors' correlated trading pattern contribute to serial correlation in daily return. The general conclusion is that institutional trading causes both permanent and temporary daily price effects.

Edelen and Warner (2001) focus on the aggregate level and suggest that the aggregate flow can be use to study the aggregate price effect of institutional trading. They study the relation between market returns and aggregate flow into the U.S. equity funds using daily flow data. Their tests show that the concurrent positive relation reflects fund flow and institutional trading affecting returns. This daily relation is similar in magnitude to the price impact reported for an individual institution's trades in a stock. The aggregate flow also follows market returns with a one-day lag. The lagged

[29] See Chan and Lakonishok (1993) and Holthausen, Leftwich and Mayers (1987).

response of flow suggests either a common response of both returns and flow to new information, or positive feedback trading. However, all the research mentioned hasn't studied any impact of institutions on the second moment of stock prices.

For researchers the main question of interest in institutions is whether institutions destabilize or stabilize security prices. The effect of rational speculators' trades is to move prices in the direction of fundamentals. While risk aversion keeps rational speculators from taking large positions, noise traders can affect prices. Rational investors dampen noise trading and prevent noise traders from driving the prices beyond the fundamental. Hence, rational speculators must stabilize asset prices.

However, this is not always the case if noise traders follow feedback strategies that they buy stocks when prices rise and sell them when prices fall. Delong et al. (1990) argue that rational speculation can destabilize the asset prices when there exists positive feedback trading. Rational speculators, for instance, trade on good news that they obtain in this period. Informed rational traders buy more in this period because they recognize that the initial price increase will simulate buying by positive feedback traders next period. And it drives prices up in this period more than fundamental news warrants. So the trading generated by positive traders drive prices beyond fundamentals in next period and destabilizes prices although rational speculators dampen them and stabilize prices. They conclude that trading by rational speculators destabilizes prices because it triggers positive feedback trading by other investors. Their conclusion is consistent with Hart and Kreps (1986)'s work[30]. However, the phenomenon of the market destabilized by positive feedback trading is not always the case. If such kind of trading drives stock prices toward fundamental rather than away from fundamental, it may not destabilize the market.

Gabaix et al. (2006) present a model in which volatility is caused by the trades of large institutions. They analyze how trading by individual large investors may create price movements that are hard to be explained by fundamental news. Institutional investors appear to be important for the low-frequency movements of equity prices. In

[30] However, Hart and Kreps assume that competitive rational speculators are the only investors able to perform physical storage. Speculators can change commodity supply in a way that makes equilibrium prices more volatile. Hence, in their model, price-destabilizing speculation results from the effect of storage on quantities.

their theory, spikes in trading volume and returns are created by a combination of news and the trades by large investors. Suppose news or proprietary analysis induces a large investor to trade a particular stock. Since his desired trading volume is then a significant proportion of daily turnover, he moderates this actual trading volume to avoid paying too much in price impact. The optimal volume will nonetheless remain large enough to induce a significant price change. They find that price movements reflect both the intensity of the perceived mispricing and the size of fund. It means that a large price movement can come from an extreme signal or the trade of a large fund. Therefore, in term of this theory the extreme returns occurred because some large institutions wished to make substantial trades in a short time period.

2.2 The empirical evidences of the impact of institutional trading on market prices

There are some empirical works that have been done on this topic of the impact of institutional trading on stock prices. Empirical literature finds mixed results when investigating the presence of institutional herding and positive trading. Most of literature relies on aggregate quarterly or annual institutional holding data to infer institutional trading. Nofsinger and Sias (1999) report a strong positive correlation between changes in institutional ownership and lagged returns. They conclude that institutional investors engage in positive-feedback trading since stocks institutions purchase subsequently outperform those they sell. Moreover, their results show that herding and feedback trading by institutional investors affect stock prices more than those by individual investors. Also Dennis and Strickland (2002) find strong evidence of herding. They examine the relations between quarterly ownership levels and the cross sectional volatility of stock returns and turnover. They note that stocks, which move the most during periods of market-wide volatility, are those that have relatively larger institutional holdings. Meanwhile, the stocks that move the most during these periods experience subsequent price reversals. They conclude that mutual funds and pension plan sponsors are herding together and trying to jump into rising markets or out of declining markets, thereby driving prices beyond fundamental values. Furthermore, Luo (2003) observes a similar result as those mentioned above. He shows that mutual fund investors create excess stock volatility because fund flows have a positive impact on the subsequent stock market volatility.

Lakonishok, Shleifer and Vishny (1992) use quarterly data on the holdings of 769 tax-exempt funds to evaluate the potential effect of their trading on stock prices. They find weak evidence of herding and some evidence of positive-feedback trading for smaller stocks, while just very little evidence of either herding or positive-feedback trading in larger stocks. Overall, they conclude that there is no strong evidence that institutional investors destabilize prices of individual stocks in their sample. However, they don't rule out the possibility of institutional investors destabilizing either aggregate stock prices or the prices of individual stocks using more frequent data. Warther (1995) examine the effect of money flow into mutual funds on aggregate security returns. They check two-direction relation between fund flows and aggregate returns, and find the evidence of a positive relation between flows and subsequent returns, and the evidence of a negative relation between returns and subsequent flows. However, there is no evidence that aggregate fund flows are positively related to past returns in weekly, monthly, quarterly or yearly data. This result indicates that investors don't follow the positive-feedback strategy at the aggregate level. In fact, they find that mutual fund investors appear to be somewhat contrarian in term of the evidence of a negative relation between returns and subsequent flows.

Recently, Lipson and Puckett (2005) investigate the effect of the trading behaviour of mutual funds and pension plan sponsors on prices during the period when there exist large market movements on the market. They find that institutions trade in the opposite direction of large moves. Especially, both money managers and pension plan sponsors are net sellers (net buyers) on days when markets experience large price increases (decreases). In other words, institutions are increasing their buying when market declines and increasing their selling when market rises. These results suggest that institutional investors actually supply liquidity to the market at these times and dampen the effect of trading on market volatility. And also Goetzmann and Massa (2003) examine bi-directional causality between cash flows and the volatility.

On one hand, if the market suffers from the positive feedback trading or herding, such behaviour may destabilize the market. On the other hand, if the positive feedback trading is a rational response to the market signal, or institutions herd and response to the same fundamental information, such institutional trading will stabilize the market rather than destabilize the market. Therefore, institutional positive feedback trading or institutional herding is not necessarily evidence of destabilizing the market prices.

3. Data Description

For this research, we use daily data to investigate the effect of mutual fund trading on stock prices at the aggregate level. Our empirical analysis relies on Shanghai A-Share Price Index and the Fund Index[31]. Shanghai A-Share Price Index is value-weighed market index and is composed of all A-Share stocks listed on the Shanghai Stock Exchange. And it is the most important index on the Shanghai Stock Exchange. The sample coves the period from 2nd January 1996 to 31st December 2004[32], and there are 2177 observations in total. The Fund index[33] is composed of all security investment funds listed on the Shanghai Stock Exchange. And it was launched on 9th June 2000. In the study the sample of the fund index covers the period from 9th June 2000 until 31st December 2004, and it includes 1102 observations.

The index return is defined as the logarithmic difference $R_t = 100(\ln P_t - \ln P_{t-1})$, where P_t and P_{t-1} are daily closing prices of index at t and $t-1$. We also take the natural logarithm for trading volume and turnover series. To check if returns, trading volume and turnover series are non-stationary, we use Dickey-Fuller and Augment Dickey-Fuller tests to test for unit roots. The tests reject the existence of unit roots for the considered series at 99% confidence.

Warther (1995) and Luo (2003) construct a measure of net sales, which is new sales plus exchange sales minus redemptions and exchange redemptions, to identify the net cash flow of mutual fund money into the market. However, individual fund cash flow is not available in the sample. For our research, the fund index, which is composed of all fund traded on the Shanghai Stock Exchange, is employed to show the trading behaviour of fund investors at the aggregate level. We have daily aggregate trading volume and turnover series of listed funds. The data set does not distinguish between share purchase and share redemption. It means that cash inflow and outflow also are not available in the data set. Hence, we can not follow Warther (1995) and Luo

[31] Till now, the mutual funds are allowed to invest only in A-share stocks & bonds in the market. Regulated by the Administrative Regulations for Security Investment Funds, the money used to invest A-share stocks may not be more than 80% of the mutual fund's total asset; high liquidities, such as cash and bonds may not be less than 20% of its total asset. Therefore, Shanghai A-Share Stock Index is employed to describe the aggregate market prices rather than Shanghai Composite Index, which is a value-weighted market index composed of all A-Share and B-Share Stocks listed on the Shanghai Stock Exchange.

[32] All the data used in this paper are downloaded from www.stockstar.com.

[33] The Fund Index is a weighted index by shares issued. The base day of Fund Index is 8th May 2000 and the base value is 1000.

(2003)'s idea to construct such kind of variable to describe fund flow. Busse (1999) mentions that fund manager expect investors invest less into the funds or even withdraw money from the funds when the market volatility is higher than average. If fund investors negatively response to market volatility and fund manager able to predict this pattern, fund managers would decrease market exposure and hold more cash. Hence, larger changes in the aggregate trading volume and turnover of listed funds indicate larger money flow into the market. Therefore, the aggregate trading volume and turnover of listed mutual fund are used as alternative proxies for the aggregate fund cash flow, respectively.

Figure 3.1 and figure 3.2 display the autocorrelation function of the daily aggregate trading volume and turnover of mutual funds traded on the Shanghai Stock Exchange. They show that there exists a substantial autocorrelation of the trading volume and turnover series, respectively. And the lagged autocorrelation in these two series implies that they are quite consistent. Hence, we decompose these two series into the predictable component and the unpredictable component. We conduct an autoregressive model for each series to separate each series into expected part and unexpected part since these two components may have the different impacts on the market prices. Table 3.1 presents estimates of regression models of trading volume and turnover of mutual fund on their own lagged variables. Panel A and panel B are the results for trading volume and turnover series, respectively. The first four lagged variables are statistically significant and the fifth lag is insignificant. F-statistics are used to test the null hypothesis that there is the absence of autocorrelation of the residuals. The results show that residuals are significantly auto-correlated in regression model I, II and III. And the null hypothesis of the absence of autocorrelation of the residuals is accepted in the last two regression tests. Hence, based on the discussion above we run an AR (4) model to estimate expected aggregate trading volume and turnover of mutual funds and the residuals are the unexpected components. We find that these expected components and unexpected components have different impacts on the market volatility, which we will explain in section 5.

4. Methodology

4.1 GARCH model

As an emerging market, Chinese stock market is more volatile compared with mature markets. In the end of the 1990s, government implemented a set of plans and policies to encourage institutional investors, e.g. mutual funds, to participate on the stock market. Hence, the mutual fund industry gradually grew and the fund index was first reported on June 2000. Moreover, during the period from January 1996 until May 2000, listed funds raised 3.03 billion RMB and the funds raised increased to 9.25 billion RMB from June 2000 to the end of 2004. This implies that fund investors actively trade on the market and mutual funds become important player after June 2000. Also it seems a signal of significant entrance of fund investors on the market. The appearance of large fund traders and the resulting increase in institutional ownership allows us to investigate the impact on the volatility of stock returns. Therefore, we employ a GARCH (1, 1) model to describe the market volatility pattern. A time dummy variable is involved in the model to capture the change in stock returns and the volatility of stock returns after 9th June 2000 when fund index was first reported.

Our empirical study on the fund investors' influence on stock market volatility relies on the following GARCH (1, 1) model with dummies:

$$R_t = \omega + \theta_1 R_{t-1} + \theta_2 D_t + \varepsilon_t \quad (3.1)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma D_t \quad (3.2)$$

$D_t = 1$ after 9th June 2000; 0 otherwise

where R_t is the return of A-Share Price Index and the error term ε_t denotes the unpredictable component of index return with mean zero and conditional variance h_t. And the dummy variable D_t is set at 0 before 9th June 2000 and 1 after 9th June 2000, when the fund index was first reported. The first equation is the mean equation, which is a function of its first own lagged variable, dummy variable and an error term. The second equation shows market volatility, which is a function of the lagged squared residual from mean equation, past conditional variance of the residual ε_t and dummy variable. In equation (3.1), the dummy variable is included to replicate the structural change in index return after fund investors significantly trading on the market. Statistically significant coefficient θ_2 indicates a structural change in the patter of stock returns after 9th June 2000. In equation (3.2), the dummy variable is used to detect the impact of fund trading on the volatility of the market. If fund traders have an influence on the volatility structure of index return, the coefficient γ should be statistically significant. The estimated coefficient γ provides a measure of the shift in the conditional volatility process. If the coefficient γ is statistically positively significant, it means that mutual fund trading destabilize the market price and increases the market volatility. On the contrary, a statistically significant and negative γ implies that fund trading contributes to market volatility and stabilizes the market prices.

4.2 Fund flows and Market volatility

In order to get a clear picture of the impact of fund trading on stock prices, we try to detect the relation between past fund flows and the market volatility. In order to examine the impact of stock fund flows on the subsequent stock market volatility, as an attempt, Luo (2003) regresses monthly volatility series on current and lagged net-flow of each fund group. We construct a GARCH (1, 1) model to check this issue. In the model, fund flow as one exogenous variable is included, gauging the impact of fund trading on changes in market volatility. Moreover, as we have discussed in section 3, daily trading volume and turnover of mutual fund are used as proxy for the daily aggregate fund flow. Hence, trading volume and turnover will be included in the model as an exogenous variable in our experiments, respectively. The model is shown as following:

$$R_t = \omega + \theta_1 R_{t-1} + \theta_2 V_{t-1} + \varepsilon_t \text{ or } R_t = \omega + \theta_1 R_{t-1} + \theta_2 T_{t-1} + \varepsilon_t \quad (3.3)$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma V_{t-1} \text{ or } h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma T_{t-1} \quad (3.4)$$

where R_t represents the return of A-Share Price Index; V_{t-1} and T_{t-1} denote aggregate trading volume and turnover of mutual fund at time $t-1$, respectively.

Regression (3.3) is used to study the relation between past fund flow and market return. And Regression (3.4) looks more closely at the question of whether fund trading destabilizes the market. A significant and positive γ implies that aggregate fund flow contributes to market volatility and destabilizes the market prices. On the contrary, if the coefficient γ is statistically negative significant, it shows that past fund flow reduces market volatility and stabilizes the market.

5. Empirical results

5.1 GARCH model with a time dummy variable

There are 1075 observations from 2nd January 1996 until 8th June 2000 and are 1102 observations from 9th June 2000 through 31st December 2004. Figure 3.3 illustrates the return of A-Share Price Index. It is obvious that market index returns fluctuate in a narrow band after June 2000 compared with the period before. It shows that before June 2000 the market is more volatile than after that.

Table 3.2 reports the empirical findings for A-Share Price Index relying on the 9th June 2000 dummy. On that day the fund index was launched on the Shanghai Stock Exchange, this event might deliver such kind of information to the public that it is a signal of significant entrance for fund investors on the stock market, and mutual funds become an important player on the market. If this is the case, our concern is whether the day event of launching fund index affects the stock prices and result in structural change in market return and the volatility of market return. The dummy variable is statistically significant in both mean and conditional volatility equation. The coefficient θ_2 is negatively significant at the 95% confidence level. It means that after June 2000 the market return is lower than it before June 2000. Figure 3.4 is the time series plots of natural logarithm of closing price of A-Share Price Index during the period from 2nd January 1996 to 31st December 2004. It is obvious that the market experienced an increasing trend from January 1999 to July 2001. Hence, the upward time trend may contributes the high index return before June 2000. And it may not imply that fund flow is negatively correlated with market return. When looking at the estimated coefficients describing conditional volatility process of the GARCH (1, 1) model with a dummy variable, the GARCH effect coefficients are statistically significant. More importantly the parameter of the dummy variable in the conditional volatility process $\hat{\gamma}$ is statistically significant at the 95% level and negative. It indicates that the volatility of the market return is reduced after June 2000. We may conclude, based on our findings that the event of launching fund index significantly affects stock market volatility, and the market-wide volatility is reduced when fund investors play important role on the market. Also we perform the robustness check in terms of different cut-off dates for the dummy variable D_t.[34] And the findings of the different dummy variables confirm the empirical results as we report in table 3.2. These results support the statements that the conditional volatility of market index returns is reduced after the significant entrance of mutual funds, and the behaviour of mutual fund trading does not destabilize stock prices at the aggregate level.

5.2 The impact of fund flows on the market price

In order to get more direct evidence of the relation between fund flow and stock prices, we reconstruct the GARCH (1, 1) model to verify this issue. Daily aggregate trading volume and daily aggregate turnover of fund listed on Shanghai Stock Exchange are used as proxies for the daily aggregate fund flow. Hence, lagged values of trading volume and turnover are included in the GARCH (1, 1) model as exogenous variable, respectively. The empirical results are shown in table 3.3 and table 3.4, respectively.

From column A of table 3.3, we find that the coefficient θ_2 is positively significant at the 99% level in mean equation. This provides the direct evidence of the positive relation between the lagged trading volume of listed fund and market index return. Also all the coefficients in the conditional volatility process of market return are statistically significant. The coefficient γ is negatively statistically significant at the 95% confidence level. It means that past aggregate trading volume has negative impact on the stock market volatility. Furthermore, in terms of the analysis above in section 3, there exists a substantial autocorrelation of the trading volume series. And the lagged autocorrelation in the series implies that it is quite consistent. Hence, column B and panel C show the results of the GARCH (1, 1) model with exogenous variable when we replace the trading volume by the expected trading volume and unexpected trading volume. Column B of table 3.3 shows that past expected component of trading volume still is positively correlated with the market return and it contributes to the market volatility and reduces the volatility of the market return at the 90% confidence level. The results in column C are similar to the findings we have from column A and B except for the one that unexpected past trading volume is not significantly correlated with market return.

[34] The results for robust check are not shown in the paper and they are available for request.

Table 3.4 presents the results of the GARCH (1, 1) model in which daily aggregate turnover is included as a proxy for fund flow. All findings are the similar to the results we have in table 3.3. The coefficients of the lagged turnover of mutual funds are negatively statistically significant, and they show that the turnover of listed mutual funds has negative impact on the stock market volatility.

Up to now, all the empirical results obtained are based on the GARCH (1, 1) in which the first-order lagged value of aggregate trading volume and turnover are involved. If a high-order lagged value is involved as an exogenous variable, we still get the similar results. However, if we run a GARCH model associated with the concurrent value[35] of these two series, the results are slightly different. Table 3.5 and 3.6 show the estimations of the GARCH model in which concurrent trading and turnover are involved so to detect the concurrent relation between the fund flow and equity prices. Column A in table 3.5 shows that aggregate market returns are strongly and positively related to the concurrent aggregate trading volume of mutual funds. And the conditional volatility of market returns is negatively related to the concurrent aggregate trading volume of mutual funds, but the coefficient γ is insignificant. Column B and C show results of the other two cases if the concurrent aggregate trading is decomposed into expected concurrent trading volume and unexpected concurrent trading volume. We find that market returns and the conditional variance of market returns are positively and negatively significantly correlated with the current trading volume of funds, respectively. However, the conditional market volatility is strongly and positively related to the unexpected concurrent trading volume. It implies that unexpected concurrent trading volume destabilizes the market. Also we have the similar findings in table 3.6 if aggregate turnover of funds is involved. It seems that expected concurrent fund flows stabilize the market and unexpected concurrent fund flows destabilize the market, and the overall impact of current fund flows on market volatility is negatively insignificant. However, the past fund flows are negatively related to market volatility. This suggests that past fund flows are acting as instruments for expected concurrent flows. This finding is similar to the one achieved by Warther (1995).

[35] In Copeland and Zhang (2003)'s study, contemporaneous volume is involved in EGARCH to measure the impact of concurrent trading activity on the market volatility.

So far we find that fund flows do affect the market volatility on Shanghai stock market and the market volatility negatively responds to past fund flows. However, these findings are not consistent with the previous research. Luo (2003), for instance, studies the relation between fund flows and stock market volatility to examine how investors react to market volatility. He finds a strong positive impact of fund flow on the subsequent stock market volatility. And Goetzmann and Massa (2003) find a positive correlation between inflows and returns and a negative one between outflows and returns.

In summary, the study of fund flows in the period of 9th June 2000 through 31st December 2004 shows that the aggregate trading volume and turnover of mutual funds have a significant negative impact on the subsequent market volatility. This finding does not support the null hypothesis that institutional trading destabilizes the market prices. Also we examine the relation between fund flows and the market index return. We find that both trading volume and turnover of mutual funds listed on Shanghai Stock Exchange in our sample are positively correlated with market index return. Due to the fact that trading volume and turnover are aggregate data, we do not distinguish these two series generated by buyers from those generated by sellers. Thus, we may not conclude from our empirical results that on Chinese market aggregate fund investors follow positive feedback strategy or negative feedback strategy, selling (buying) shares when the market is down and buying (selling) shares when the market is up. A more appropriate way to examine the impact of fund flows on the market volatility is to decompose flow data into inflows and outflows and to study their relation with market volatility separately. Moreover, Demirer and Kutan (2004) examine the presence of herd formation on the Chinese markets using individual firm level as well as sector level data and find that herding formation does not exist on Chinese markets. So their evidences support our findings.

6. Herding behaviour

The empirical results show that the past fund flows is negatively correlated with the volatility of the stock return and stabilizes the market prices on Shanghai Stock Market. In most theoretical literature it is argued that herding and positive-feedback trading are the two resources to destabilize the market prices. However, the evidence is not exclusive. Demirer and Kutan (2004) conclude that there is no evidence to support the presence of herd formation in firm level, sector level and market level data from the Shanghai and Shenzhen Stock Exchanges, while in our study, we focus on the trading generated by fund investors. Thus, we check whether there is the presence of herding formation by fund investors in Shanghai Stock Market. We follow the methodology used by Christie and Huang (1995), Chang, Cheng and Khorana (2000).

They mention herd behaviour as an obvious intent by investors to mimic the behaviour of other investors. The testing method proposed by Christie and Huang (1995) is based on the idea that investors are more likely to suppress their own beliefs in favor of the market consensus during large price changes, so herd behaviour is most likely to emerge during such periods[36]. Hence, equity return dispersions around aggregate market return are used to test formation of herding during periods of the presence of large market movement. Then, we should expect significantly lower dispersions in individual security returns as investors are drawn to consensus of the market. However, according to rational asset models the prediction disagrees with the above argument. Rational asset models predict that the dispersion will increase with the absolute value return since individual assets differ in their sensitivity to the market return. Hence, if the results are in favor of the rational asset pricing theory, we expect significantly higher dispersions and they imply that there is no the evidence for the existence of herding formation.

Christie and Huang (1995) suggest the use of cross-sectional standard deviation of returns as a measure of equity return dispersions to detect the herding behaviour. We concentrate on the behaviour of fund investors. That means that we just need to describe the dispersion of fund index return around market return. Hence, we

[36] Chang, Cheng and Khorana (2000) also follow the same idea to test herd behaviour in international equities.

construct a variable as a measure of return dispersion, which is defined as the squared difference between fund index return and market index return:

$$Df_t = (R_{ft} - R_{mt})^2 \quad (3.5)$$

where R_{ft} and R_{mt} are the returns of fund index and A-share price index at time t, respectively. This methodology suggests that the presence of herd behaviour is most likely to occur during periods of extreme market movements, as they would most likely tend to go with the market consensus. Hence we estimate the following linear regression model:

$$Df_t = \mu + \gamma_1 D_t^L + \gamma_2 D_t^U + \varepsilon_t \quad (3.6)$$

where $D_t^L = 1$, if the market index return on time t lies in the 1% (5%) lower tail of the return distribution, 0, otherwise.
$D_t^U = 1$, if the market index return on time t lays in the 1% (5%) upper tail of the return distribution, 0, otherwise.

We define an extreme market return as the same as the one by Chang, Cheng and Khorana (2000), and Demirer and Kutan (2004) that lies in the 1% (5%) lower or upper tail of the return distribution. If there is the presence of herding formation by fund investors, the coefficients γ_1 and γ_2 are expected to be negative and statistically significant. Table 3.7 presents the empirical results of regression model (3.6). All coefficients are positive and significantly significant at the 99% level. Our results are consistent with prior research that we do not find any evidence in favor of herding formation during period of large market movements. The positive coefficient γ_1 and γ_2 indicate that the return dispersion increases when the market experiences large market change. This finding supports rational asset pricing models which suggest that periods of large market movements induce incremental levels of dispersion as individual returns differ in their sensitivity to the market returns. Goetzmann and Massa (2003) provide a similar explanation. They regress fund inflows and outflows on implied volatility of the market index. Due to the positive relation between fund flows and the implied volatility, it seems consistent with the idea of an increase in the dispersion of beliefs among small investors rather than the mean-variance model of investor decision-making. Moreover, based on the data of changes in quarterly holding of individual stocks, Lakonishok, Shleifer and Vishny (1992) find that there only exits very little herding by institutional investors in their sample. However, it does not support the hypothesis of the presence of herding formation. They point out that institutions are not destabilizing the prices of individual stocks they trade under the most common definition of destabilizing speculation.

We test the presence of herding formation by fund investors in this section and our empirical result does not support the hypothesis of the existence of herding behaviour. Perhaps we should not be surprised at this result. Our result is consistent with the finding by Wermers (1999). He finds little evidence of herding by mutual funds in the average stock. However, he finds a much higher level of herding in small stocks and among growth oriented mutual funds. In this chapter, we use the fund index to investigate the impact of fund investors on equity prices at the aggregate level rather than using individual fund dataset. Considering the existence of herding behaviour on individual stocks, the phenomenon may be less likely to be detected on the market as a whole because investors may use various trading styles that result in uncorrelated trading decision on average. Therefore, we conclude that fund investors do not seem to herd too much in Shanghai Stock Market at the aggregate level and this finding supports our result presented in section 5, which is that the trading generated by fund investors does not destabilize market prices on the Shanghai Stock Market.

7. Conclusion and Summary

It is still an open debate on the Chinese stock market what is the impact of institutional trading on stock prices. If institutions herd together and follow positively feedback strategy, the trading generated by institutions may destabilize the market. However, empirical findings on institutional investors' herding and positive feedback trading behaviour are not necessary evidence in favor of the destabilizing effect on stock prices. By studying the relation between fund flows and the market volatility we have a better understanding of mutual fund investors' behaviour, not only of their reaction to past market performances, but also of their attitude to investment risk at the aggregate level. In this chapter, we show that on daily frequency the behaviour of investors in mutual funds turns out to be somewhat different from the one in mature markets. The investors' behaviour appears to relate to measures of market volatility.

We examine the impact of fund trading on stock prices using daily data at the aggregate level. Shanghai A-Share Price Index and the Fund Index are employed and cover the period of 2nd January 1996 to 31st December 2004. The Fund index was first announced on the Shanghai Stock Exchange on 9th June 2000 and it could be regarded as an indicator that mutual funds play an important role. We analyse the mutual fund behaviour through studying the fund index. We construct a GARCH (1, 1) model with a time dummy variable to detect the structural change in mean and volatility of market returns. We find that the market-wide volatility is reduced after June 2000, and this provides direct evidence of fund trading stabilizing financial market.

Also we check the relation between fund flows and the market price index to detect the impact of fund flows on stock prices. Using the GARCH (1, 1) model, the results show that the aggregate trading volume and turnover of listed funds are positively correlated with subsequent index return and negatively correlated with subsequent conditional volatility. It seems that the behaviour of mutual funds contributes negatively to the market volatility on the Chinese market. Due to the lack of fund inflow and outflow data, we can not conclude whether fund investors follow positive feedback strategy or negative feedback strategy on the Chinese market. While, the absence of herding formation by fund investors supports our empirical finding that trading generated by fund investors does not destabilize the market prices.

In addition, further argument can be made based on other characteristics of the Chinese stock market, which may partially are attributed to our empirical results. First, mutual fund industry is heavily regulated by the government. The China Securities Regulatory Commission (CSRC) maintains significant mechanisms of influence over the funds, since it approves the appointments of fund management firm's CEOs and the fund manager themselves, and thereby can retain some influence over their trading strategies and the market indices. Obviously, however, as the market grows in size, this becomes more difficult.

Second, the finding of institutional trading not destabilizing the stock market might come from the absence of the equity derivative market in China. Derivatives provide an opportunity for investors to hedge their position. The availability of derivatives as hedging vehicles makes investment in riskier stocks more attractive and this leads to increase the demand for the underlying assets. However, the existence of equity derivative market may destabilize the stock market price. If the market price increases, for instance, institutions purchase more shares to set up a delta-neutral position. Then it might induce positive feedback trading and destabilize the market price, and vice versa. Hence, we need further research to investigate whether or not the absence of derivative market result in institutional trading not destabilizing the market price.

Chapter Four: What can we learn from the equity derivative market: evidences from the Chinese derivative market?

1. Introduction

In a complete market, with no transaction costs and trading constraints, a stock option is regarded as a redundant security, as its payoff can be synthesized by combining a position in the underlying stock with risk-free lending and borrowing. However, in the real world, where dynamic trading strategies replicating option payoffs are infinitely costly, introducing options may have an impact on the underlying asset stock prices and their variances. So one popular question is whether derivative introduction affects the volatility of the related markets.

In theories, the impacts of option listing are still controversial. On one hand, Detemple and Selden (1991) show that the introduction of an option results in an increase in the stock price and a decrease in the volatility of the stock return because of investors' different assessments about the downside potential of the stock in a quadratic utility setting. As argued by Grossman (1988), the price of a traded option can convey information that would be unobservable in an economy where the option can only be replicated. So the information released by new traders may have a stabilizing effect on the stock market. In addition, option trading seems to make the underlying asset adjust more rapidly to new information, and trading volume tends to be increased by option trading. On the other hand, Back (1993) finds that the introduction of options does not change the expected average level of volatility although the trading of options conveys information as Grossman (1998) argues. While Harris (1989) voices that theoretical analyses of the derivative contracts trading effect on the volatility of the underlying asset lead to conflicting conclusions. He shows that trading in derivatives may stabilize or destabilize the underlying market, and the effect depends upon what assumptions were made.

Also, empirical investigations in the effects of a derivative listing on the underlying asset are inconclusive. Such as Skinner (1989), Conard (1989), Bollen (1998)[37] and Hwang and Satchell (2000) find a significant reduction in the variance of underlying stocks following derivative introduction. Whilst, Hernandez-Trillo (1999) and Mazouz (2004) figure out that on average the introduction of derivatives doesn't change the volatility level.

Moreover, option markets are often viewed as markets for volatility trading. Option prices provide forecasts of the future average variance of returns from the underlying asset over the life of the option. The ability of the volatility forecast implied by options prices to predict future volatility is considered as a measure of the information content of option prices. Day and Lewis (1992) using S&P 100 index options, and Lamoureux and Lastrapes (1993) using individual equity options, find that the implied volatility contains useful information in forecasting volatility, but also that time-series models contain incremental information to the implied volatility. But, Canina and Figlewski (1993) challenge, arguing that the S&P 100 implied volatility is such a poor forecast that it is dominated by the historical volatility. To explore the relative performance of implied and historical volatility predictors, Xu and Taylor (1995) employ ARCH models and show that implied volatilities provide specifications for daily conditional variances which can not be significantly improved by using past returns. From the recent studies by Christensen and Prabhala (1998) and Fleming (1998), the evidence favors the conclusion that implied volatilities are more informative than daily returns when forecasting equity volatility. Also Jorion (1995) and Xu and Taylor (1995) obtain the similar conclusion in the foreign exchange market but with more certainty.

Most literature in this topic was based on option and future markets. In this paper, we investigate the impact of warrant introduction[38] on the underlying stock and the

[37] Bollen (1998) summarizes the reasons why one could expect a reduction in the variance of the underlying stock after option introduction. (1) This is a requirement and must be met in order to list an option in exchange (e.g. Skinner, 1989); (2) Due to the fact that option introductions may attract new informed traders to trade, the variance of underlying stock is expected to fall; (3) Market maker might hedge their risk more efficiently after option introductions and narrow the bid-ask spread in the stock market so that the variance of stock return may decrease (Fedenia and Grammatikos, 1992).

[38] Alkeback and Hagelin (1998), and Chan and Wei (2001) explore price and liquidity effects associated with derivative warrant issuance on the Stockholm Stock Exchange and the Stock Exchange of Hong Kong, respectively using the approach of event study. So our research in this paper is different from previous studies.

information content of implied volatility of warrant. We are interested in warrants for the reason that warrants are used, typically in conjunction with bonds and/or stocks, as vehicle to finance the activity of a firm. Warrants are more complicated to value than regular stock options because warrants cause dilution and normally are long lived. After warrants were banned in 1995 due to excessive speculation, the first financial derivatives traded on Shanghai Stock Exchange was issued on 22nd August 2005 because the government wanted to support its pilot program to dispose of non-tradable shares through the issue of warrants. Hence, the impact of derivatives listing on the underlying stock becomes one of most important topics for both researchers and participants on the market.

The other contribution in this paper is that we employ a GARCH model of associated with cross-sectional market and industry volatility to explore the effect of warrant listing on the underlying stock, instead of using a conventional GARCH model or constructing a control group to investigate this effect within the traditional literature. The change in the volatility of an individual stock may result from market and industry influence instead of warrant listing as shown by Campbell, Lettau, Malkiel and Xu (2001). They argue that market and industry volatility are two important components of individual stock volatility. We find that the warrant introduction reduces the stock volatility without the removal of other factors, but it has no significant impact on the volatility of the underlying stock when market and industry influence are considered. In addition, we examine the relations between realized volatility, implied volatility and historical volatility. The empirical findings show that implied volatility of warrants contains incremental information for realized volatility. But, implied volatility doesn't subsume the information contained in all other variables in the market information set in explaining future volatility and it is not informationally efficient.

The chapter is organized as follows. In section 2, literature on the impact of derivative listing upon the underlying asset and information content of implied volatility is reviewed. In section 3, we describe the information about data set and the method of computing implied volatility. Empirical methodology is introduced in section 4. The empirical results are reported in section 5. Section 6 is the concluding remarks.

2. Literature Review

2.1 The effect of derivative listing on the underlying stock

2.1.1 Theoretical Literature

The impact of option listing is still controversial amongst the academia. Researchers provide several theoretical arguments, supporting both the view that option listing decreases the volatility of the underlying stock, and the opposite view that option listing has destabilizing effect on the volatility of the underlying stocks. Others show that on average the option listing may not have significant impact on the volatility of stock return.

As argued by Grossman (1988), the price of a traded option can convey information that would be unobservable in an economy where the option can only be replicated. An option that appears redundant, in the sense that it can be dynamically replicated, might not actually be redundant, since introducing it might convey information that will change state prices. He concludes that a new option contract generally increases the liquidity of the underlying stocks, and the information released by new traders may have a stabilizing effect on the stock market. This argument, of course, is based on the possibility that the price of traded options conveys the demand for securities and removes the uncertainty regarding the cost of obtaining an option-like payoff.

Back (1993) shows that the introduction of options causes volatility to be stochastic, however, this does not change the expected average level of volatility. The basic intuition underlying Back's model is similar to that of Grossman's: option trading conveys information not available in a similar market where that may be synthesized with dynamic strategy.

Even though an option may be replicable before it is introduced, it does not mean that introducing an option has no effect on the spot asset. Detemple and Selden (1991) find the introduction of options leads to an increase in the equilibrium price and a reduction in the stock's volatility when they examine the case where agents have quadratic utility and the heterogeneity of their beliefs. Moreover, John, Koticha and Subrahmanyam (1993) examine the simultaneous trading of a stock and option in the presence of informed investors using the sequential order arrival framework. Comparing the resulting equilibrium to the case without options trading, it is shown that the introduction of options leads to an improvement in liquidity and a reduction of volatility in the underlying stock market, but stock prices become less informative.

In contrast to above statements, Harris (1989) voices that theoretical analyses of the effect of trade in derivative contracts on the volatility of the underlying assets lead to conflicting conclusions, depending upon what assumptions are made. An increase in well-informed speculative trade has two opposite effects on measured volatility. It decreases volatility because informed traders provide liquidity, and it increases volatility due to new fundamental information since the information is adopted by prices more quickly.

2.1.2 Empirical Literature

In the literature, there exist some empirical studies on the effect of option introduction upon the underlying assets. That means that most of the studies focus on the option market and less work has been on the warrant market, where this paper is going to fill the gap.

To provide new and comprehensive evidence on whether stock options have a beneficial[39] or a harmful effect on the market for the underlying securities, Kumar, Sarin and Shastri (1998) conduct an empirical analysis of the impact of options trading upon the market quality of the underlying market. Their study empirically examines the impact of stock option listings on several aspects of the market quality of the underlying stocks, such as the variance of the pricing error, liquidity, i.e. the bid-ask spread, quoted depth, trading volume and trading frequency, etc. They find that option listings improve liquidity, and result in a lower level of information asymmetry and the reduction in the variance of the pricing error. Overall, the results suggest that the option listings have a beneficial impact of the market quality for the

[39] They list the three main reasons why option listing may have a beneficial impact on the quality of the underlying asset. First, option trading improves the efficiency of incomplete asset market and reduces the volatility of the underlying market. Second, option listings may cause informed investors to migrate to the option market so the decrease in the proportion of informed investors in the underlying market lower the adverse selection cost of the market maker and improves liquidity. Third, option trading makes the underlying market more efficient because it increases the level of public information in the market.

underlying stocks in terms of higher liquidity, lower information asymmetry and greater pricing efficiency. Recently, a similar research is done by Jong, Koedijk and Schnitzlein (2004), who perform a controlled experiment to investigate the informational linkages between stock market and option market. They examine the hypothesis that the presence of an option improves the market quality of the underlying asset by permitting the effective sharing of price discovery across markets. Moreover, Mazouz (2004) follow the methodology proposed by Antonious and Holmes (1995) to test the impact of option listing on the rate at which information is incorporated into the stock price.[40]

Hasbrouck (1993) suggests that an overall measure of market quality is the variance of the pricing error (defined as the difference between the observed price and the efficient price), with low variance implying a market of high quality. A decrease in the variance of the pricing error would be evidence of greater pricing efficiency. His results suggest that the underlying stock prices become more efficient after the advent of options trading. The decrease in the variance of the pricing error is consistent with the notion that the trading of options increases the price efficiency in the underlying market.

Moreover, Hwang and Sachell (2000) decompose the FTSE100 stock index related volatility into transitory noise and unobserved fundamental volatility. They argue that the information, which affects the fundamentals of the underlying asset, is the same across all derivatives of the asset and results in the same fundamental volatility. It is natural to assume that there is only one fundamental volatility defined over the underlying asset and all derivatives based on the underlying asset, although there are many volatilities related to only one underlying asset. They find that introducing European options reduces fundamental volatility, while transitory noise in the

[40] This analysis is based on the GARCH model. Under the GARCH (p, q) framework, the constant is interpreted as the permanent variance component, the squared lagged error terms reflects of impact of the arrival of recent information, and the lagged conditional variance may be thought of the arrival of old information. α_i and β_i are the coefficient of the squared lagged terms and the lagged conditional variance, respectively. When separating the estimation of GARCH process across pre-and post- option listing periods, if there is any increase in α_i for $i = 1, 2, \cdots, p$, after option listing, β_i is expected to decrease in post-listing period because an increase in α_i indicates an increase in the speed at which the information is incorporated into the stock price and it reduces the uncertainty regarding old news, and vice versa.

underlying and futures markets does not show significant changes. They conclude that, for the FTSE100 index, introducing a new options market has stabilised both the underlying and existing derivative markets.

Bollen (1998) investigate the impact of option introductions on the return variance of underlying stocks. Previous research generally finds a significant reduction in stock return variance following the listing of options. Bollen (1998) employ a large sample to compare changes in return variance of option stocks with changes in the return variance of a control group. Finally, he concludes that option introductions do not significantly affect stock return variance since the average change in the control group[41] is statistically indistinguishable from the average change in the optioned stocks since stocks with option introductions exhibit an average change in variance that is equivalent to the average change in a control group. Also Lamoureux (1991) finds that there is no change in volatility on average. These findings are consistent with Back (1993)'s study in which the volatility of the underlying asset does not change on average when the option is introduced.

In terms of methodologies, Skinner (1989) addresses this problem generating an empirical distribution of market adjusted variance ratios but he does not take into account the fact that variance changes over time. In order to correct this problem, Hernandez-Trillo (1999) use ARCH and GARCH models to examine the volatility effect associated with listing warrants on the individual stocks on the Mexican market. The difference of Hernandez-Trillo (1999)'s work with the others is that he addresses the problem that varies systematically through time for individual firms as their leverage, investment opportunities and other characteristics change. Furthermore, he uses an approach by French, Schwert and Stambaugh (1987)[42] to adjust the return to eliminate the possibility of the impact of changes in market volatility on changes in individual stock volatility around the time of option listing.

[41] Bollen (1998) constructs the control group by matching the optioned stocks one-for-one with control stocks in the same trading location and industry to eliminate the market-wide and industry-wide influence on the variance of individual stock return. He uses GMM by Hansen (1982) to estimate the parameter.

[42] In that approach, an estimate of daily market volatility is used to standardize the daily stock return.

2.2 The information content of implied volatility

Option markets are often viewed as markets for volatility trading. Option prices provide forecasts of the future average variance of returns from the underlying asset over the life of the option. The ability of the volatility forecast implied by options prices to predict future volatility is considered a measure of the information content of option prices.

Day and Lewis (1992), using S&P 100 index options, and Lamoureux and Lastrapes (1993), using individual equity options, find that the implied volatility contains useful information in forecasting volatility, but also that time-series models contain incremental information to the implied volatility. Both studies conclude that implied volatility is biased and inefficient: past volatility contains predictive information about future volatility beyond that contained in implied volatility. While, Jorion (1995) reports that implied volatility is an efficient (though biased) predictor of future return volatility for foreign currency futures.

Canina and Figleski (1993) find implied volatility to be a poor forecast of subsequent realized volatility. In aggregate and across subsamples separated by maturity and strike price, implied volatility has virtually no correlation with future volatility, and it does not incorporate the information contained in recent observed volatility. They show that implied volatility is an inefficient and biased forecast of realized future volatility that does not impound the information contained in recent historical volatility. While, the Black-Scholes implied volatility can be thought of as volatility forecast, it can also be interpreted as a measure of an option's price, which controls for option-specific characteristics such as the moneyness of an option, time to expiry, etc. In option pricing theory, option price should be positively correlated with the underlying asset's volatility, i.e. Bergman, Grundy and Wiener (1996). Thus Canina and Figlewski (1993)'s findings, that there is no significant relation between an option's price (implied volatility) and future realized volatility, appears to be inconsistent with option price theory.

In contrast, Christensen and Prabhala (1998) find that implied volatility outperforms past volatility in forecasting future volatility and even subsumes the information content of past volatility in some of their specifications. They show that implied volatility is a less biased forecast of future volatility than the results of the previous studies. This difference could be attributed to their use of longer volatility time series. They find that past volatility has much less explanatory power than reported in Canina and Figlewski (1993). And Christensen and Prabhala (1998) argue that the difference results from the different sample procedure because of the use of the overlapping data in Canina and Figlewski (1993). However, Christensen and Prabhala (1998) construct a nonoverlapping data set with exactly one implied volatility and one realized volatility covering each time period in their sample.

Fleming (1998) examines the performance of the S&P 100 implied volatility as a forecast of future stock market volatility. The results indicate that the implied volatility is an upward biased forecast, but also that it contains relevant information regarding future volatility. Despite the implied volatility's bias, a linear model using the implied volatility appears to provide a good quality forecast of ex post volatility. Also he examines the efficiency of implied volatility, where efficiency refers to informational efficiency relative to past forecast errors. He finds that the implied volatility is efficient with respect to its past forecast error and its forecast errors are orthogonal to the information set. The implied volatility dominates the historical volatility in terms of ex ante forecasting power and none of the information variables frequently used to model conditional volatility can explain the component of volatility that is unexplained by the implied volatility.

In addition, previous studies of low-frequency (daily or weekly) index returns and implied volatilities have produced conflicting conclusions about the informational efficiency of the S&P 100 option market. Blair, Poon, and Taylor (2001) do the empirical analysis using ARCH models and find no evidence for incremental information in daily index returns beyond that provided by the VIX index of implied volatilities. Their conclusions are in agreement with the studies done by Christensen and Prebhala (1998) and Fleming (1998). In their study, they extend the historic information set to include high-frequency (5-min) returns. Although high-frequency returns are highly informative about future volatility, they show that there appears to be only minor incremental information in high-frequency returns, and this information is almost subsumed by implied volatilities.

3. Data and the Implied Volatility

3.1 The nature of the Chinese equity derivative market

Warrant is one kind of derivatives, but it is different from options. A firm rather than other investors supplies warrants. Warrants are used, typically in conjunction with bonds and/or stocks, as a vehicle to finance the activity of a firm. The rationality for using warrant is based on the existence of market imperfections. Since warrants are used as a financial vehicle, they are likely to change the capital structure, in contrast to stock options. It means that warrants are issued by a firm on its own stock. When warrants are exercised, the firm receives the exercise price and the size of the corporate pie increases. The firm then issues additional shares with the result that the corporate pie is cut into more pieces. So warrants, as derivatives and financial vehicles, have a rather complicated influence on the firm.

As known, two-third shares of listed companies are not tradable on the Chinese secondary stock market. The effort to sell non-tradable shares, after the failure of the first attempt in the year 2001, was revived in April 2005 for the purpose to finance a patchy welfare system and enhance transparency. China's securities regulator allows all the national publicly traded companies to give shares, stock options and warrants to directors, senior managers and other employees. This implies that the government wants to support its pilot programme to dispose of nontradable shares through the issue of warrants. Hence, SHANGHAI - Baoshan Iron and Steel Co. Ltd., the listed arm of China's top steel maker, listed warrants on the Shanghai stock exchange on 22nd August 2005[43]. It is the first financial derivatives traded on the country's bourses since 1995 and is a one-year contract. Baoshan's warrants are being issued by the company itself as part of a plan to compensate investors for allowing the company's non-tradable shares to be listed on the Shanghai market. The Chinese securities regulators would also have to help create an over-the-counter market for stock options, a prerequisite for warrant issuers to hedge their exposure to the volatility of these instruments.

[43] Up to 23rd August 2006, 18 warrants were listed, in which 17 out of 18 were European style warrants and one was American style. And so far, all were one-year contracts.

3.2 Data

Daily closing prices of Baoshan Steel for the period from August 2004 to August 2006 are used, which includes 453 observations. Daily excess return is evaluated as logarithm return above the risk-free rate. Information on Baoshan Iron and Steel Co. Ltd. issuing warrants is acquired from the Shanghai Stock Exchange. The series of the warrant prices is obtained from the data centre of Shanghai Stock Exchange, which contains 243 observations from 22nd August 2005 to 23rd August 2006.

To control the impact of other factors on the underlying stock, market-wide and industry-wide influences are taken into account. The SHSE-50 stock index, which consists of 50 individual stocks, is regarded as a proxy for market index for the research presented in this chapter. The construction of SHSE-50 index is based on the characteristics of individual stocks such as the size of market capitalization and liquidity, and these sample stocks represent large listed companies traded on the Shanghai Stock Exchange. The steel industry index is not reported on the Shanghai Stock Exchange. So we must derive the industry index by matching the stocks traded on the Shanghai Stock Exchange as identified by the first two digits of the Listed Companies Classification and Code (LCCC) issued by China Securities Regulatory Commission (CSRC).

3.3 The implied volatility

3.3.1 Estimation of implied volatility

Warrants are more complicated to value than regular stock options because warrants cause dilution and normally are long lived. With some adjustments for the impact of dilution, the Black-Scholes call option model can be used to value European warrants issued by a company on its own stock[44]. Without the consideration of dividends, warrant pricing model is given by

$$W=\left(\frac{N}{N/\gamma+M}\right)\left[\left(S+\frac{M}{N}W\right)N\left(d_1\right)-Xe^{-rt}N\left(d_2\right)\right], \qquad (4.1)$$

where

[44] See Galai and Schneller (1978), Lauterach and Schultz (1990), and Veld (2000).

$$d_1 = \frac{\ln\left(\frac{S+(M/N)W}{X}\right)+rT}{\sigma\sqrt{T}} + \frac{\sigma\sqrt{T}}{2}$$

$$d_2 = d_1 - \sigma\sqrt{T}$$

At any instant of time, W is the warrant price; S is the price of the underlying stock; X is the exercise price; N is the number of outstanding shares of stock; M is the number of warrants issued by a firm; γ is the number of shares that can be purchased with each warrant; r is the risk-free interest rate which is continuous and constant through time; T is the time to expiration; σ is the standard deviation of the value of the shares plus the warrants; $N(d_i)$ is the cumulative normal density function evaluated at d_i.

Comparing the dilution adjusted Black-Scholes model with the original Black-Scholes model, three modifications are made to incorporate dilution. First, the stock price, S, is replaced by $S+(M/N)W$. Second, σ in the adjusted formula is the standard deviation of the equity of the firm rather than for the stock return. Third, the formula is multiplied by $N/((N/\gamma)+M)$.

As discussed above, three modifications are made to generate warrant pricing model which is based on the Black-Scholes model. Veld (2000) summarises that three possibilities exist, for the dilution correction: (1) the use of a dilution corrected option valuation model; (2) the use of an option valuation model not corrected for dilution; and (3) the use of an option valuation model only multiplied by the dilution factor. Crouhy and Galai (1991) note that in practice warrant prices are often calculated by multiplying the outcome from the original Black-Scholes model by the dilution factor and it results in a downwards biased outcome.

Hull and White (1987) generate option model associated with a stochastic volatility. It might be argued that implied volatility from stochastic volatility models appears less biased than the implied volatility from Black-Scholes model, and more appropriate than the implied volatility from Black-Scholes model. However, it is necessary to make an assumption about an explicit volatility process, which might not be true. The implied volatility from stochastic volatility pricing model may be biased resulting from the misspecification in the underlying stochastic process. Therefore, we use a dilution-adjusted version of the Black-Scholes model to estimate implied equity volatility in this study.

3.3.2 Measurement errors in the implied volatility

Implied volatility is considered to be the market's forecast for the volatility of the underlying asset of a warrant. To calculate the implied volatility, a warrant valuation model and observed warrant prices are needed as inputs. So, in addition to the problem with the identification of the true warrant pricing model, we also have measurement errors in implied volatility, such as inappropriate use of risk-free interest rates, and/or dividends. The potential problems arise from the Black-Scholes model's assumptions about the stochastic process followed by the underlying variables. These problems might be more acute for warrants than options because of warrants' long lives. Firstly, the dilution-adjusted Black-Scholes assumes a constant equity variance. Secondly, another possible deficiency in the Black-Scholes model arises from its assumption of a constant default free interest rate. Thirdly, another institutional factor not incorporated in the Black-Scholes model is the potential for extension[45]. Fourthly, the implied volatility is the implied volatility of the equity.

Measurement error is problematic due to infrequent trading, which results in the mismatch between the times when the stock and warrant markets close. Consider what happens when the warrant trades less frequently than the underlying stock, the observed warrant price is determined when the market price of the underlying stock differs from its observed closing price. If the stock price increases (decreases) after the last warrant trade, implied volatility will tend to be downward (upward) biased.

Moreover, converting a warrant price into an implied volatility incurs errors due to bid/ask spreads and non-continuous prices. Generally speaking, in many studies[46]

[45] See Longstaff (1990) and Lauterbach and Schultz (1990). For instance, Lauterbach and Schultz (1990) show a case in which some firms want to extend warrants to avoid taxation because the Internal Revenue Service ruled that if a warrant expires worthless, the initial price of the warrant is taxable income for the firm.
[46] See Day and Lewis (1992), Canina and Figlewski (1993), Christensen and Prabhala (1998).

implied volatilities contain relevant measurement errors whose magnitudes are unknown.

4. Empirical Methodology

Existed empirical studies have used different methodologies to assess the problem of our interest. Jennings and Starks (1986) determine the effect of earnings announcements on stock price change variability by employing PW variance test. Skinner (1989) forms two variance ratios for each firm. The first one is the estimated variance ratio, ex post and ex ante of the listing, and the second one is a similar ratio adjusted for market volatility. He also checks Wilcoxon signed-rank test. Freund et al. (1994) perform a variance regression analysis which is applied to changes in stock residuals variance upon option introduction. In this chapter we go with a different method.

We proceed in the following manner. First, we generate time-series measure of stock return volatility through GARCH process as defined in Bollerslev (1986). Bollerslev et al. (1992) review these applications. Then we use a dummy to differentiate the derivatives introduction so to verify the impact of derivatives introduction on stock market. In particular, the methodology allows us to identify if this effect is permanent. Second, a modified GARCH model - GARCHX, which is GARCH model with cross-sectional market and industry volatility, is employed to explore the derivative listing effect after controlling for the effect of factors other than derivative listing. Third, we apply time-series models to study the information content of implied volatility.

4.1 GARCH model and the warrant listing effect

We model the time varying variance using the GARCH process by Bollerslev (1986), which provides a more flexible and parsimonious approximation to conditional variance dynamics.

Suppose stock return r_t can be modelled as

$$\phi(L)r_t = \theta(L)\varepsilon_t \quad (4.2)$$

where $\phi(L)$ and $\theta(L)$ are polynomials, L is the lag operator and ε_t is the white noise with constant variance, σ^2. When the errors are heteroskedastic rather than homoskedastic, Engle (1982) proposes ARCH model to describe the characteristics of time varying variance. Based on Engle's work, Bollerslev (1986) generates generalised ARCH (GARCH). The GARCH (p, q) process, in which the conditional variance of the error term is a linear function of the lagged squared residuals and the lagged residual conditional variance, is modelled in the following manner:

$$r_t | I_{t-1} \sim N(X\gamma, h_t)$$
$$\varepsilon_t = u_t \sqrt{h_t}$$
$$h_t = h(\varepsilon_{t-1}^2, \varepsilon_{t-2}^2, \cdots, \varepsilon_{t-p}^2, h_{t-1}, h_{t-2}, \cdots, h_{t-q}, \alpha) \quad (4.3)$$

where X is a linear combination of lagged endogenous and exogenous variables with a vector of unknown parameters γ, I_{t-1} indicates the information set at time $t-1$, and u_t is a white noise process with zero mean and constant variance, i.e. $E(u_t) = 0$ and $Var(u_t) = 1$, p and q are the lag lengths for the squared residual ε_t^2 and the residual conditional variance h_t, respectively.

In this chapter, we focus on GARCH (1, 1)[47] model, which is specified in the following manner:

$$r_t = \mu + \varepsilon_t$$
$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D \quad (4.4)$$

where, D is the time dummy variable. For a GARCH process to be well-defined, both α_i and β_i should be non-negative and the sum of coefficients α_1 and β_1 of equation (4.4) must be less than unity[48]. On the other hand, if it equals to one, the model

[47] Bollerslev et al. (1992) shows that GARCH (1, 1) is widely used and it can capture volatility clustering in financial data. Moreover, Antonios and Holmes (1995) show that GARCH (1, 1) process is the most parsimonious representation of the variance in terms of log likelihood ration tests.

[48] In the conventional GARCH (1, 1) model, one major problem is the non-negativity condition. Since it is a conditional variance, its value must always be strictly positive; a negative variance at any point in time would be meaningless. In order to ensure that these always result in positive conditional variance estimates, all of coefficients in the conditional variance are usually required to be non-negative. However, the non-negativity conditions may be violated by the estimated model. In fact, this is a sufficient but not necessary condition for non-negative of the conditional variance. Hence, in this paper, we may impose less strong restrictions on the GARCH model when we do the estimation, i.e. stationary and the sum of alpha and beta is positive.

specification is characterised by non-stationary variable, such that any shock to the variable of a process is permanent[49].

The dummy coefficient δ_1 is the determinant of the warrant listing impact on the return volatility of the underlying stock. If the dummy is statistically significant, then the existence of warrant trading has had an impact on the stock market volatility. A significant positive (negative) sign of δ_1 indicates a permanent increase (a permanent decrease) in the volatility of the underlying stock after warrant listing.

4.2 GARCH model with cross-sectional market and industry volatility

We argue that the change in the volatility of the underlying asset might result from other factors rather than warrant listing across warrant listing periods. These factors include changes in market-wide and/or industry-wide conditions as well as the endogenous nature of the warrant listing decision. Campbell, Lettau, Malkiel and Xu (2001), for example, decompose the total volatility of a stock into three components, market volatility, industry volatility and firm specific volatility, and show that the market volatility is an important component of the stock return and tends to lead the idiosyncratic volatility. Connor, Korajczyk and Linton (2006) and Jones (2001) also suggest that there is common heteroskedasticity in asset specific returns.

Following Bollen (1998) and Mayhew and Mihov (2000)'s studies, Mazouz (2004) use a control sample to account for possible changes, across option listing periods, in either the volatility and/or the speed at which information is incorporated into the stock prices, caused by factors other than option listing. These factors include changes in market-wide and/or industry-wide conditions and the endogenous nature of the option listing decision. The control sample is selected by matching each optioned stock with a control stock from the same industry sector, with a similar size and pre-option listing volatility of returns. Then he examines whether the changes, across pre- and post-option listing periods, in the volatility and the speed at which information is incorporated into the stock price are the same for both the sample of optioned stocks and the control sample. If the control group exhibits an average in variance that equals

[49] See Engle and Bollerslev (1986).

the average change in the optioned sample, it means that the option listing do not affect stock return variance on the average. However, the drawback of the control group comparison is that different criteria in formulating the control group may result in different results. In other words, it may suffer from the control group selection bias since this method is subject to judgment of researcher on the criteria to construct a control group.

Based on Hwang and Satchell (2001) GARCHX[50] model, which is the GARCH model with cross-sectional market volatility, we add a new factor, cross-sectional industry volatility, on the model we use in this chapter. That is to say, our GARCH model is a model, associated with cross-sectional market and industry volatility as controls, to examine the impact of warrant listing upon the underlying stock. Consider the following cross-sectional relationship between the return of asset i and the market-wide portfolio and J factors[51]:

$$r_{it} = \gamma_{0i} + \gamma_{mli} r_{mlt} + \gamma_{1i} x_{1t} + \cdots + \gamma_{Ji} x_{Jt} + v_{it} \quad (4.5)$$

where r_{mlt} and x_{jt} are the market-wide return and the j th factor for $j = 1,2,\cdots,J$, and γ_{0i}, γ_{mli}, γ_{ji} are parameters, and v_{it} is the error term with zero mean and variance, σ_{iv}^2. Hwang and Satchell (2001) mention that those factors may be of macroeconomy, and of firm specific characteristics. They assume that the explanatory variables are

[50] Hwang and Satchell (2001, 2004) explain the time-series expectation for time-series statistics and the cross-sectional expectation for cross-sectional statistics, for instance, mean and variance. For any variable x_{it}, where $i = 1,2,\cdots,N$ and $t = 1,2,\cdots,T$, the time series expectation and the cross-sectional expectation are defined as $E^T(x_{it}) = \frac{1}{T}\sum_{t=1}^{T} x_{it}$ for $t = 1,2,\cdots,T$ and $E^C(x_{it}) = \sum_{i=1}^{N} w_{it} x_{it}$ for $i = 1,2,\cdots,N$, respectively, where w_{it} is a cross-sectional weight on asset i at time t. They mention that w_{it} may be a probability measure if $w_{it} \geq 0$ for all i and t, and $\sum_{i=1}^{N} w_{it} = 1$ for all t. In a portfolio, for example, w_{it} equals to $\frac{1}{N}$ if the cross-sectional expectation is an equally weighted average, and w_{it} is the ratio of market value of individual asset i to the market value of the portfolio at time t if it is valued weighted moment. And the variance of the cross-sectional series is

$$Var(x_{it}) = \sum_{i=1}^{N} w_{it}\left(x_{it} - E^C\left(x_{it}\right)\right)^2.$$

[51] Linear factor models become popular. If the return process is under this framework, volatility of a stock is cross-sectional decomposed into multiple components of the factors.

orthogonal in conventional linear factor models. Then, they show the volatility of the return on asset i at time t given information set I_{t-1}:

$$\left(r_{it} - E_{t-1}^{T}\left(r_{it}\left|I_{t-1}\right.\right)\right)^2 = \gamma_{mli}^2\left(r_{mlt} - E_{t-1}^{T}\left(r_{mlt}\left|I_{t-1}\right.\right)\right)^2 + \gamma_{1i}^2\left(x_{1t} - E_{t-1}^{T}\left(x_{1t}\left|I_{t-1}\right.\right)\right)^2 + \cdots + \gamma_{Ji}^2\left(x_{Jt} - E_{t-1}^{T}\left(x_{Jt}\left|I_{t-1}\right.\right)\right)^2 + v_{it}^2 \quad (4.6)$$

which indicates the cross-sectional relationship between individual asset's time-series volatility and factor volatility.

Even though the cross-sectional average of γ_{mli} and γ_{ji} are expected to be one and zero[52], the coefficients on factors other than the market-wide factor are not significantly different from zero in many cases. However, Hwang and Satchell (2001) point out that γ_{mli}^2 may still be significant and γ_{ji}^2 may not be significant. Hence, under the assumption that the market is rational, they approximate asset i's return volatility with the following cross-sectional relationship with market volatility

$$\left(r_{it} - E_{t-1}^{T}\left(r_{it}\left|I_{t-1}\right.\right)\right)^2 \approx \gamma_{mli}^2\left(r_{mlt} - E_{t-1}^{T}\left(r_{mlt}\left|I_{t-1}\right.\right)\right)^2 + v_{it}^2. \quad (4.7)$$

Campbell, Lettau, Malkiel and Xu (2001) show that market volatility, industry volatility and firm asset specific volatility are the important components for the explanation of individual asset volatility. However, in the study by Hwang and Satchell (2001), only the market-wide factor was under consideration and the industry volatility was not involved. In order to control for effects of factors other than warrant listing on the return volatility of the underlying asset, we extend Hwang and Satchell (2001) model to the one in which both market-wide and industry volatility are considered. Then, under the assumption that the market-wide factor and other factors are orthogonal, the equation (4.7) becomes

$$\left(r_{it} - E_{t-1}^{T}\left(r_{it}\left|I_{t-1}\right.\right)\right)^2 \approx \gamma_{mli}^2\left(r_{mlt} - E_{t-1}^{T}\left(r_{mlt}\left|I_{t-1}\right.\right)\right)^2 + \gamma_{Ili}^2\left(r_{Ilt} - E_{t-1}^{T}\left(r_{Ilt}\left|I_{t-1}\right.\right)\right)^2 + v_{it}^2 \quad (4.8)$$

[52] See Hwang and Salmon (2004).

where r_{II} is the industry level return at time t.

In the sense of the discussion above, the market and industry volatility should be included in the GARCH model because both are the important components in volatility. However, in the conventional GARCH model, those two factors are not involved. Moreover, Andersen and Bollerslev (1998) show that the time-series market volatility is highly noisy in the GARCH framework[53]. Then Hwang and Satchell (2001, 2004) suggest that the cross-sectional market volatility might be involved rather than the time-series market volatility because the cross-sectional market volatility is more informative than the time-series market volatility and highly persistent,[54]. Hence, the GARCHX model is used in this chapter to examine the effect of warrant listing upon the volatility of the underlying asset after controlling the market and industry level volatility, which is shown as

$$r_t = \mu + \varepsilon_t$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D + \delta_2 \sigma_{C,ml,t-1}^2 + \delta_3 \sigma_{C,II,t-1}^2 \quad (4.9)$$

where D is the time dummy variable, and $\sigma_{C,ml,t}^2$ and $\sigma_{C,II,t}^2$ are the cross-sectional market and industry volatility, which are defined as

$$\sigma_{C,ml,t}^2 = \sum_{i=1}^{N} w_{it} \left(r_{it} - E^C \left(r_{it} \right) \right)^2, \quad (4.10)$$

and $$\sigma_{C,II,t}^2 = \sum_{i=1}^{N} w_{it} \left(r_{it} - E^C \left(r_{it} \right) \right)^2. \quad (4.11)$$

[53] Andersen and Bollerslev (1998) prove that regression methods will give low R^2 values when daily squared returns measure realized volatility, even for optimal GARCH forecasts, because squared returns are noisy estimates of volatility.

[54] Hwang and Satchell (2004) compare the properties of cross-sectional and time-series volatility using the UK and US data set. The results show that cross-sectional market volatility is not only highly correlated with time-series market volatility but also more informative than squared market returns, and suggest that cross-sectional market volatility can be useful for the explanation and forecasting of time-series market volatility. Overall, the results support cross-sectional volatility as a proxy measure of time-series volatility.

Based on the equation (4.9), in which the influences of the market and industry factors are removed, if the coefficient, δ_1, is statistically significant, it means that the existence of warrant trading has its impact on the volatility of the underlying stock. Otherwise, warrant listing does not affect the stock volatility. The change in the stock volatility may be resulted from the change in market or industry volatility.

4.3 The information content of implied volatility

In literature, option implied volatilities provide market information about the expected return volatility of the underlying asset for the period until the expiry date of option. However, implied volatility may be biased representation of market expectations. For example, if volatility risk is priced or transaction prices do not represent equilibrium, market prices or the option pricing model is mis-specified. Despite of these concerns, implied volatilities have often been found to be a better volatility forecast than those given by historical price models which use low-frequency returns.

In this chapter, warrant implied volatilities are obtained from the dilution-adjusted Black-Scholes model, in which three modifications have been made on the original Black-Scholes model. Implied volatility represents an ex-ante volatility forecast. Whilst; the implied volatility of warrant is the future expectation of the volatility of the equity instead of the expectation of the volatility of the underlying stock over the remaining life of warrant. This is the difference between the warrant implied volatility and the option implied volatility.

Firstly, in the spirit of the work by Day and Lewis (1992), we check whether past implied volatility is useful to predict the conditional volatility of the underlying stock.

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \kappa IV_{t-1} \quad (4.12)$$

where IV_{t-1} is the implied volatility at time $t-1$. Equation (4.12) is the expression of the conditional variance in GARCH (1, 1) model. Therefore, the past implied volatility contains the information about the conditional variance of the underlying stock if the coefficient, κ, is statistically different from zero.

Secondly, we construct a regression model to test predictive power since the implied volatility is wildly believed to be the best available forecast of the volatility of returns over the remaining contract life. So, we regress the realized volatility on forecast volatility in order to explore the predictive power of implied volatility:

$$RV_t = \theta_0 + \theta_1 IV_t + \eta_t \quad (4.13)$$

where RV_t denotes the realized volatility at time t and η_t is the error term. The realized volatility is the ex-post return volatility over the warrant's life. This is computed as the sample standard deviation of the daily log returns over the remaining life of the warrant.

$$RV_t = \sqrt{\frac{1}{T-t}\sum_{k=t}^{T}\left(r_k - \bar{r}\right)^2} \qquad (4.14)$$

where r_k is the stock return at time t, $\bar{r}$ is the sample mean of r_k, and $T-t$ is the number of days to expiration.

Option prices will provide optimal predictions of volatility when option markets use information efficiently and the pricing model correctly specifies the relationship between prices and volatility expectations. Information other than option prices should not have incremental predictive power when this joint hypothesis is true. So if implied volatility has the predictive power for future volatility, θ_1 is expected to be nonzero[55]. And the issue of whether other information has the predictive power is tested below.

Finally, we estimate the following multiple regression to compare the information content of implied volatility with that of historical volatility:

[55] In this case, we are unable to test whether implied volatility is an unbiased forecast of realized volatility. If implied volatility is an unbiased forecast of realized volatility, θ_0 and θ_1 should be equal to 0 and 1, respectively. However, as we mentioned before, the implied volatility of warrant is the future expectation of the equity and θ_0 may be non-zero. Hence, implied volatility of warrant is not an unbiased forecast of realized volatility of the underlying stock.

$$RV_t = \theta_0 + \theta_1 IV_t + \theta_2 HV_{t-1} + \eta_t \quad (4.15)$$

where HV_{t-1} is historical volatility at time $t-1$, and η_t is the error term. In this case, historical volatility is the standard deviation of the log return of the underlying asset over the 20-day period preceding the date of the implied volatility. A 20-day sample period is used for historical volatility because it is approximately equal to the number of trading days per month. That is

$$HV_t = \sqrt{\frac{1}{20}\sum_{k=t-19}^{t}\left(r_k - \bar{r}\right)^2} \quad (4.16)$$

where r_k is the daily log return of the stock, and $\bar{r}$ is the sample mean of r_k.

As discussion in section 3, measurement error is problematic so the OLS estimators will be inconsistent and typically lead to an incorrect conclusion. Two sources of errors can affect implied volatility estimates. To a certain extent, specification error exists when market prices of warrants are different from the assumed valuation model, and estimation error exists when bid/ask price effects and infrequent trading among stocks causes the observed option price to differ from its theoretical value. However, the magnitudes of errors in implied volatility are unknown. Fleming (1998) does not correct the measurement errors in implied volatility, while Christensen and Prabhala (1998) show that past implied volatility is a natural candidate for an instrument because it is correlated with true time implied volatility but is plausibly unrelated to measurement errors. Hence, in order to correct for error-in-variables, we employ past implied volatility as an instrumental variable to estimate the regression model.

In addition, if implied volatility is the market's prediction of actual volatility over the time remaining to a warrant's expiration date, daily observations on implied volatility involve sequential forecasts for overlapping time periods. This leads to serial dependence in forecast errors, and to a statistical problem when testing the model because the overlapping problem with error terms results in downward bias in the OLS standard errors. In previous studies, researchers deal with this problem through aggregating and excluding data to create non-overlapping observations[56]. Unfortunately, such procedures can severely reduce the power of statistical tests. Instead, we employ the estimation procedure proposed by Hansen (1982)[57] to deal with this problem. Under this procedure, the estimated covariance matrix for the coefficients is

$$\Omega = \left(X'X\right)^{-1} \Psi \left(X'X\right), \quad (4.17)$$

where Ψ is defined as

$$\hat{\Psi} = T^{-1}\sum_t \eta_t^2 X_t' X_t + T^{-1}\sum_m \sum_t Q(m,t)\hat{\eta}_m \hat{\eta}_t \left(X_t' X_m + X_m' X_t\right), \quad (4.18)$$

where $\hat{\eta}_t$ and $\hat{\eta}_m$ are the residuals from the OLS regression model. $Q(m,t)$ is an indicator function taking the value 1 if there is an overlap between returns at time m and t, and zero otherwise.

[56] Furthermore, as discussed in Canina and Figlewski (1993), simultaneous trading in multiple contracts with different strike prices and overlapping expirations creates further cross-correlations if the data sample contains observations on more than one option per day. In this study, we don't suffer from this problem because only one contract is traded during the sample period.

[57] Both Canina and Figlewski (1993), and Jorion (1995) apply this method to volatility forecast.

5. Empirical Results

5.1 The impact of warrant listing on the volatility of the underlying stock return

Table 4.1 represents the results of the GARCH family models used in this chapter. Column A is estimates of the conventional GARCH (1, 1) model with a time dummy variable. The coefficient, δ_1, is negative and statistically different from zero at 95% confidence level. It means that the conditional variance of stock return experiences a negative shift after the warrant introduction. We may conclude that the warrant listing reduces the volatility of the underlying stock. While, the change in the volatility of the underlying asset might result from other factors rather than warrant listing across warrant listing periods. These factors include changes in market-wide and/or industry-wide conditions and the endogenous nature of the warrant listing decision. Column B shows the results of the GARCHX model associated with cross-sectional market and industry factors. In this case, the weak restriction, $\alpha_i + \beta_i \succ 0$, is involved since the non-negativity is sufficient but not necessary condition when estimating the GARCH model. Then we still get the strong GARCH effects from the table. δ_2 and δ_3 are positive and statistically significant at the 90% and 95% level, respectively. δ_1 is still negative but statistically insignificant at any significance level. It shows that market-wide and industry-wide volatility make positive contributions to the volatility of individual stock return although the impact of market volatility is just marginally significant, and the warrant introduction does not have significant effect on the individual volatility. Moreover, we notice that industry influence on individual volatility is stronger and larger than the market influence.

Our findings are in line with the arguments of Connor et al. (2006), Jones (2001), and Campbell et al. (2001). Connor et al. (2006) and Jones (2001) point out that the lagged cross-sectional volatility is an important explanatory variable in the presence of the past volatility and past conditional volatility. Campbell et al. (2001) break down the total volatility of a stock into three components, market volatility, industry volatility and firm specific volatility, and show that the market volatility is an important component of the stock return and tends to lead the idiosyncratic volatility. Compared with the result of Campbell et al. (2001), our work finds that the market volatility takes less role than the industry volatility does. This difference might come from the use of SHSE-50 Index. It only reflects the performance of those large enterprises on the exchange.

Lamoureux (1991), Hernandez-Trillo (1999), and Mazouz (2004) find that there is no change in volatility on average after the option introduction. So, our findings confirm those empirical studies above and support the Back (1993)'s argument. In Back (1993)'s model, the volatility becomes stochastic when the option is introduced, but the expected average volatility does not change. While, Kumar, Sarin and Shastri (1998) argue that the beneficial impact of option listings will be greater for lower market capitalization stocks because this is likely to have lower liquidity, lower trading volume, higher information asymmetry and lower pricing efficiency prior to option listings. Consistent with this, they find that the impact of option listings generally is greater upon lower market capitalization stocks. But we can not make direct comparison with their arguments since just one warrant has been investigated in this chapter and Baoshan Steel is a listing company with large capitalization in Shanghai Stock Exchange.

Overall, market and industry factors make significant contribution to the volatility of individual stock. After the influence of those two factors removed, the warrant listing does not affect the volatility of the underlying stock. It means that the change in the volatility of Baoshan Steel is the result from the change in market and industry volatility instead from warrant introduction across warrant listing periods.

5.2 Information content of implied volatility

Column C shows that past implied volatility of warrant has the predictive power of the conditional variance of the underlying stock since κ is positive and statistically significant at the 99% level. As argued by Day and Lewis (1992) and Lamoureux and Lastrapes (1993), they examine implied volatility as a source of information. Both studies find that IV contributes a statistically significant amount of information about volatility over the forecasting horizon covered by the models.

Table 4.2 reports the estimates of specification (4.13) and (4.15) that are used to investigate the relations between realized volatility, implied volatility and historical volatility. The second row shows that the coefficient of implied volatility is positive and statistically different from zero at the 99% level. In this case, implied volatility contains the incremental information for realized volatility. Implied volatility is informative. However, we do not test the un-biasness of implied volatility since implied volatility of warrants is different from implied volatility of options. As shown by Lauterbach and Schultz (1990), they compare three implied standard deviations (ISD), which are implied standard deviations from warrant, equity and stock options, respectively. They find that the average ISDs from the equity is larger than the ones from the other two, and the average ISDs appear larger relative to ISDs from stock options.

If historical volatility is used to predict realized volatility, it is positively correlated with realized volatility. When both implied volatility and historical volatility are involved in the model, the coefficient of implied volatility is still significant at the 99% level, but the coefficient of historical volatility is significant at 90% level. The results show that realized volatility is partly forecastable from publicly available information on historical volatility. It seems that implied volatility is not informatively efficient. However, Blair, Poon, and Taylor (2001) find that the implied volatility index VIX provides more accurate forecasts for realized volatility than the historic volatility. Although high-frequency returns are highly informative about future volatility, they show that there appears to be only minor incremental information in high-frequency returns, and this information is almost subsumed by implied volatilities. Their conclusions are also in agreement with the evidences found by Christensen and Prebhala (1998) and Fleming (1998).

Furthermore, to explore the relative performance of implied and historical volatility predictor, Xu and Taylor (1995) employ ARCH models to show that implied volatilities provide specifications for daily conditional variances on the Philadelphia Stock Exchange (PHLX). However, using data of past returns can not significantly improve their results. They show that the volatility forecast obtained from option prices is optimal, and returns from the underlying asset do not contain significant incremental information for predicting future volatility. They also show that the unbiased hypothesis can not be rejected and the slope coefficients are very close to 1 if the constant term is not involved. However, in our study presented in this chapter, past historical volatility still has the predictive power for realized volatility.

Based on the discussion above, the empirical findings show that implied volatility of warrant is informative and contains incremental information for future return volatility. However, implied volatility is not informationally efficient. Implied volatility does not subsume the information content of historical volatility and future volatility is partly forecastable from publicly available information on historical volatility.

6. Concluding remarks

In a frictionless no-arbitrage world, derivatives are redundant assets and will not affect the underlying market. However, in the real world where markets are incomplete, effects of the introduction of derivatives markets upon the underlying market exist. Moreover, option prices will provide optimal predictions of volatility when option markets use information efficiently and the pricing model correctly specifies the relationship between prices and volatility expectations since option markets are often viewed as markets for volatility trading. Information other than option prices should not have incremental predictive power when this joint hypothesis is true.

We try to detect whether the introduction of warrant affects the return variance of underlying stocks and whether implied volatility of warrant contains incremental predictive power for future return volatility. The heightened regulatory interest regarding the economic impact of derivatives on related markets provides motivation of our study. Using GARCH model with cross-sectional market-wide and industry-wide volatility, we find that the introduction of warrant does not affect the volatility of underlying stock after taking other factors into account, and the change in the individual volatility after the warrant listing results from the change in market level and industry level volatility. This finding which we research on a new perspective is consistent with those previous findings in literature taken market and industry influences into account, but they were focused on the mature markets. In the meantime, the empirical results show that implied volatility of warrant contains information for further volatility and it is informative on the Chinese derivative market. But implied volatility does not subsume the information contained in all other variables in the market information set because historical volatility still make contribution to the forecast of further volatility. This result is slightly different from the theoretical prediction.

Based on the results presented in this chapter, in the sense of policy suggestion, warrant listing may be used as a device to dispose of the non-tradable shares, as warrant listing does not increase the volatility of the underlying assets, and the implied volatility together with the historical volatility can predict the market movements.

Chapter Five: Conclusion

This thesis examines the stability of the Chinese stock market in three different aspects. In the first part of thesis, we focus on the market microstructure. We test the dynamic price-volume relation because the study of the joint dynamics of returns and volume provides a good understanding of stock price movements, which has significant implications for asset pricing models, regulators, hedgers, speculators and other participants in financial markets. First, we find a nonlinear relationship between return and trading volume on the Chinese stock market. Second, the results suggest the existence of the linear bi-directional causal relation both for the index and for six of ten stocks since causality tests can provide useful information on whether knowledge of past stock price movements improves short-run forecasts of current and future movements in trading volume, and vice versa. However, there is no significant evidence to support the nonlinear causal relation on the Shanghai market between returns and trading volume except for one individual stock only.

In China, two thirds of shares are non-tradable on the secondary market, which imposes the liquidity constraint on investors. We take this issue into account in our model by calculating adjusted stock prices and trading volumes. Then we obtain the significant evidence of nonlinear causal relation between returns and volume. The results show that the existence of liquidity constraints affects the price-volume relation, and confirm Jennings et al. (1981)'s conjecture that differences in regulation, market size and information flow affect the price-volume relation. Hence, this research sheds light on the market behaviour of stocks on the Chinese market, from which regulators and market participants may benefit. In particularly, the results of our research suggest that regulators should pay more attention to the impact of non-tradable shares because this liquidity constraint results in the change in information flows and in the price-volume relation.

The second part of the thesis investigates the impact of mutual fund trading on market prices. Due to the growing influence that institutional investors exert on the structure of capital markets, it is generally recognized that policy-makers need to take a closer look at the functioning of these institutions. The Fund index was first announced on the Shanghai Stock Exchange on 9th June 2000 and it could be regarded as an indicator that mutual funds started playing an important role. We construct a GARCH (1, 1) model with a time dummy variable to detect the structural change in mean and volatility of market returns. We find that the market-wide volatility is reduced after June 2000 and this provides direct evidence of fund trading stabilizing the financial market. Moreover, results show that the aggregate trading volume and turnover of listed funds are positively correlated with subsequent index return and negatively correlated with subsequent conditional volatility. These are evidences that mutual funds contribute to market stability and reduce market volatility on the Chinese market.

In our data set, we can not find any evidence of herding formation which is the evidence in favor of the destabilizing effect on the market prices. So, the absence of herding formation by fund investors reinforces our empirical finding that trading generated by fund investors does not destabilize market prices. In addition, other characteristics of the Chinese stock market may be attributed to our findings, such as the government influence on the mutual fund industry and the lack of the hedging mechanism. Therefore, further research is needed in this direction.

The third part of the thesis explores the impact of warrant listing on the underlying stock prices using different methods. Due to the argument that market-wide and industry-wide volatility are important components of individual stock volatility, we exploit a GARCH model associated with cross-sectional market level and industry level volatility, detecting the impact of derivative introduction on the underlying stock prices. We find that the introduction of warrants does not affect the volatility of underlying stock after taking other factors into account, and the change in the individual volatility after the warrant listing results from the change in market level and industry level volatility. In addition, empirical results show that the implied volatility of warrants contains information for further volatility and it is informative on the Chinese derivative market. But the implied volatility does not subsume the information contained in all other variables in the market information set because historical volatility still makes contribution to the forecast of future volatility. This result is slightly different from the theoretical prediction that the implied volatility is an optimal forecaster for future volatility and it subsumes all the information available on the market. Overall, the warrant introduction does not have the significant effect on the underlying asset, and the implied volatility of warrants is informative. These are good indicators for China to develop derivative markets which will complement the current financial markets.

Appendices

Table 2.1 This table reports the estimated results for the two regressions of volume against returns and absolute returns during the period of January 2002 to September 2003 in panel A and panel B, respectively. The regressions are shown as follows:

$$AV_t = \gamma_0 + \gamma_1 AR_t + u_t,$$

$$AV_t = \gamma_0 + \gamma_1 |AR_t| + u_t,$$

where AV_t and AR_t present adjusted standardized volume and returns, u_t is the error term.

	γ_0	T -statistic	γ_1	T -statistic	R^2
Panel A: Regression of volume on stock returns					
A-SHARE PRICE INDEX[a]	0.020	0.464	0.141	7.25**	0.042
SHANGHAI AIRPORT	0.038	0.371	0.170	3.93**	0.036
BAOSHAN STEEL	0.041	0.436	0.151	4.27**	0.043
HUANENG POWER	0.034	0.325	0.159	4.04**	0.039
SH CONTAINER	0.037	0.345	0.001	0.33	0.0003
SINOTRANS DEV	0.006	0.253	0.010	1.79*	0.008
TONGRENTANG	0.035	0.335	0.107	2.81**	0.019
HAIXIN GROUP	0.033	0.325	0.183	5.98**	0.080
SINOPEC CORP	0.042	0.419	0.222	5.11**	0.060
SHENERGY CO	0.041	0.403	0.208	5.35**	0.066
SHANGHAI AUTO	0.041	0.424	0.173	4.24**	0.042
Panel B: Regression of volume on absolute stock returns					
A-SHARE PRICE INDEX	-0.342	-5.12**	0.200	7.17**	0.041
SHANGHAI AIRPORT	-0.787	-5.76**	0.493	8.52**	0.150
BAOSHAN STEEL	-0.745	-6.43**	0.440	10.1**	0.200
HUANENG POWER	-0.692	-5.23**	0.413	8.34**	0.146
SH CONTAINER	-0.242	-2.15**	0.148	6.01**	0.081
SINOTRANS DEV	-0.039	-1.46	0.023	3.59**	0.030
TONGRENTANG	-0.872	-7.08**	0.498	11.0**	0.228
HAIXIN GROUP	-0.365	-2.92**	0.210	5.66**	0.073
SINOPEC CORP	-0.842	-6.62**	0.560	10.0**	0.196
SHENERGY CO	-0.740	-5.7**	0.445	9.02**	0.167
SHANGHAI AUTO	-0.805	-6.43**	0.509	9.56**	0.182

* Indicates statistical significant at the 90% level.

** Indicates statistical significant at the 99% level.

a: the sample period of A-Share Price Index is extended to December 2006.

Table 2.2 This table provides the estimated results for the regression of volume against positive and negative returns during the period of January 2002 to September 2003. The regression is shown as follows:

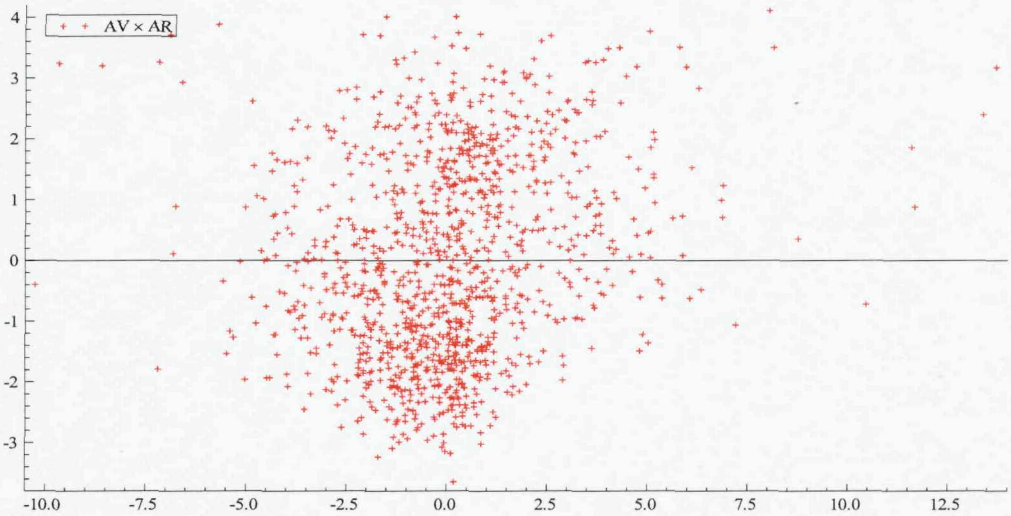
$$AV_t = \gamma_0 + \gamma_1 AR_t^+ + \gamma_2 AR_t^- + u_t,$$

where $AR_t^+ = AR_t$ if $AR_t \succ 0$ and 0 otherwise, $AR_t^- = AR_t$ if $AR_t \prec 0$ and 0 otherwise. In the regression model, AV_t and AR_t present adjusted standardized volume and returns, u_t is the error term.

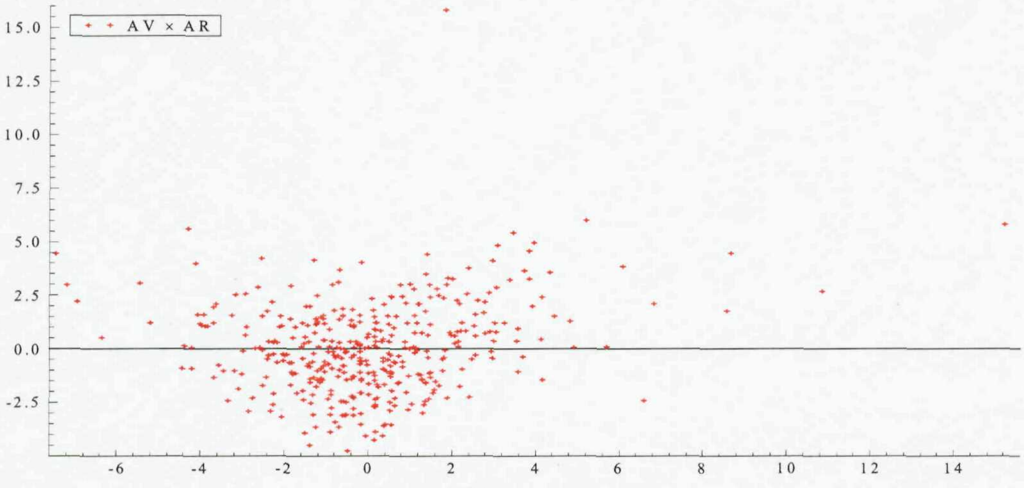
	γ_0	t-statistic	γ_1	t-statistic	γ_2	t-statistic	R^2
A-SHARE PRICE INDEX[a]	-0.30	-4.47**	0.30	9.42**	-0.10	-2.82**	0.072
SHANGHAI AIRPORT	-0.74	-5.33**	0.56	8.69**	-0.37	-4.59**	0.161
BAOSHAN STEEL	-0.70	-5.96**	0.48	9.96**	-0.35	-5.56**	0.207
HUANENG POWER	-0.612	-1.75*	0.45	8.26**	-0.33	-1.3	0.151
SH CONTAINER	-0.45	-3.95**	0.42	7.84**	-0.10	-4.00**	0.148
SINOTRANS DEV	-0.08	-2.85**	0.07	5.91**	-0.01	-1.71*	0.080
TONGREN TANG	-0.86	-6.88**	0.51	10.0**	-0.47	-7.32**	0.229
HAIXIN GROUP	-0.47	-4.04**	0.50	9.84**	-0.04	-0.96	0.193
SINOPEC CORP	-0.77	-5.91**	0.61	10.2**	-0.41	-4.97**	0.207
SHENERGY CO	-0.67	-5.15**	0.54	9.85**	-0.26	-3.82**	0.195
SHANGHAI AUTO	-0.77	-6.15**	0.61	10.0**	-0.60	-5.2**	0.203

Note: all the models pass the model significance test at 99% level.
* Indicates statistical significant at the 90% level.
** Indicates statistical significant at the 99% level.
a: the sample period of A-Share Price Index is extended to December 2006

Figure 2.1 These scatter plots display the relations of return and volume for index and ten individual stocks chosen in this paper. The adjusted standardized return and adjust standardized volume are plotted on the horizontal axis and the vertical axis, respectively.

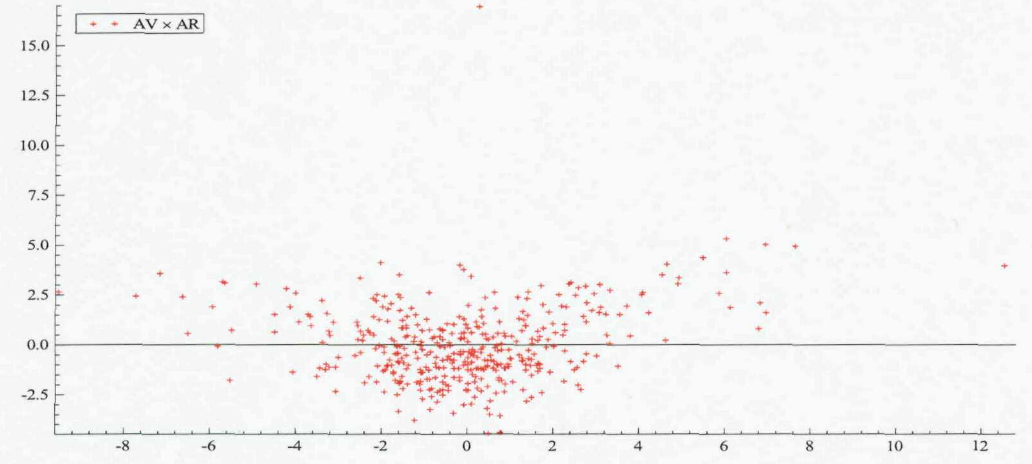


A-SHARE PRICE INDEX

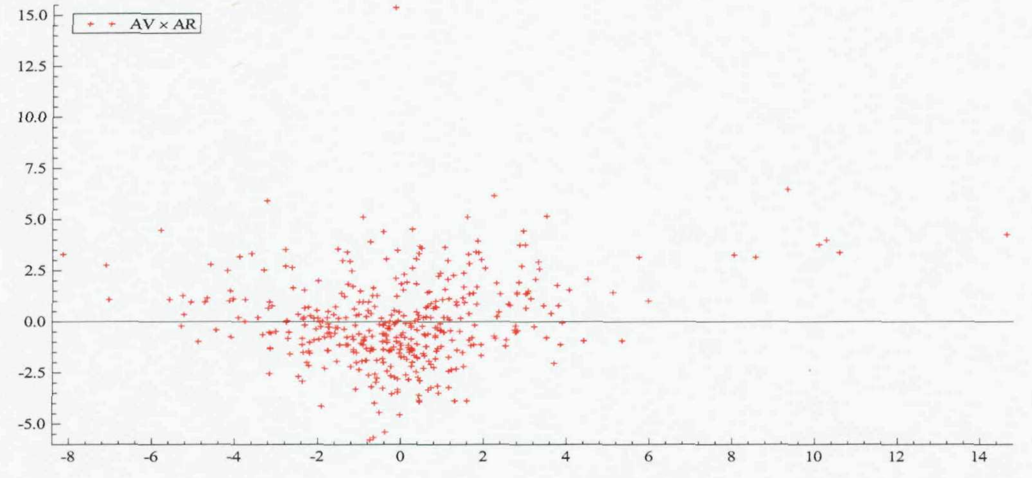


SHANGHAI AIRPORT

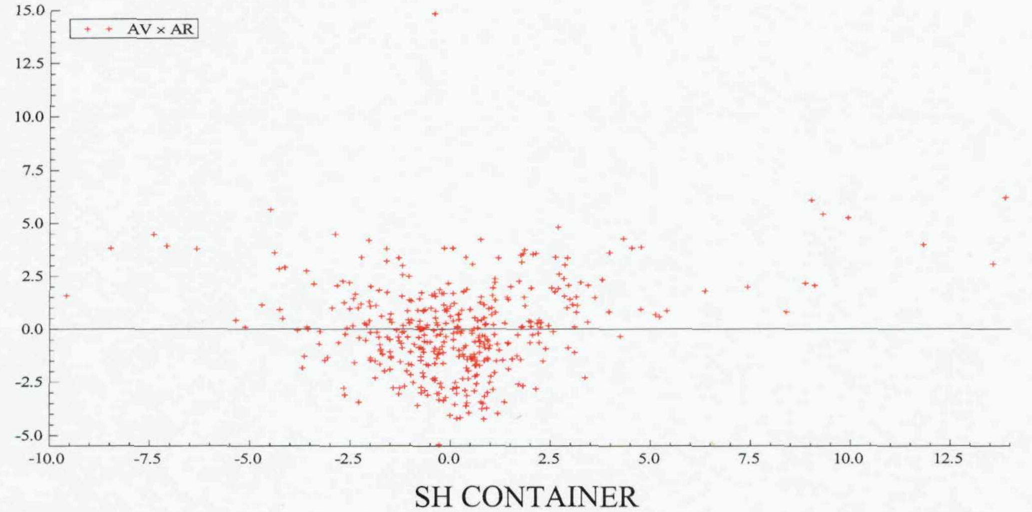
Figure 2.1 (Continued)



BAOSHAN STEEL

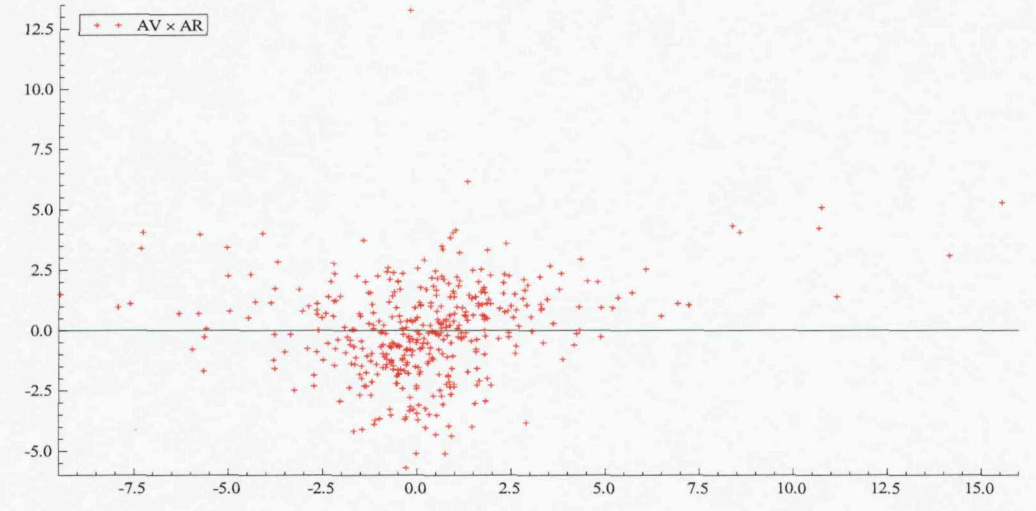


HUANENG POWER

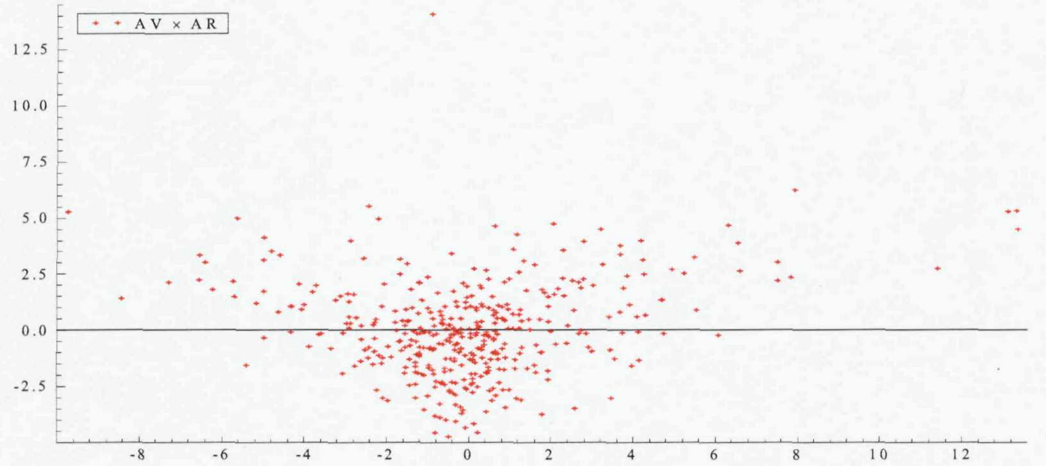


SH CONTAINER

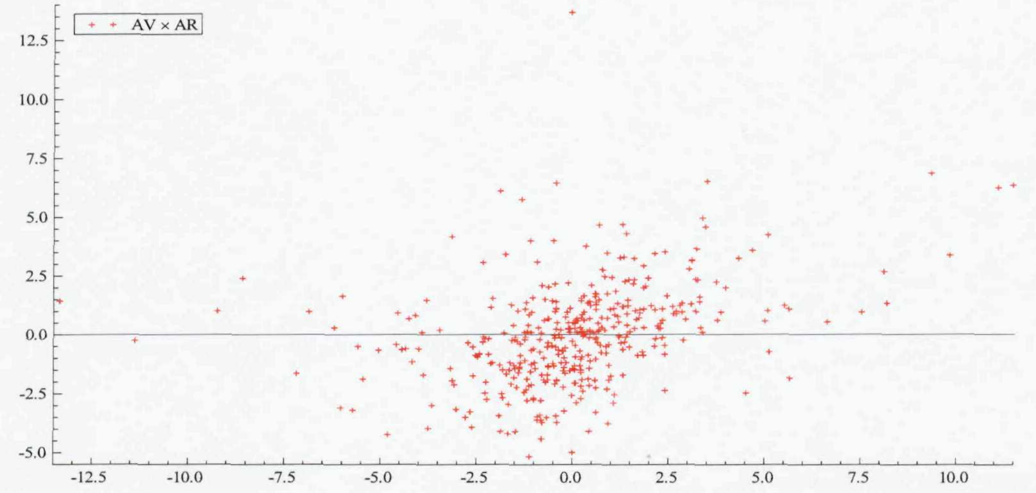
Figure 2.1 (Continued)



SINOTRANS DEV

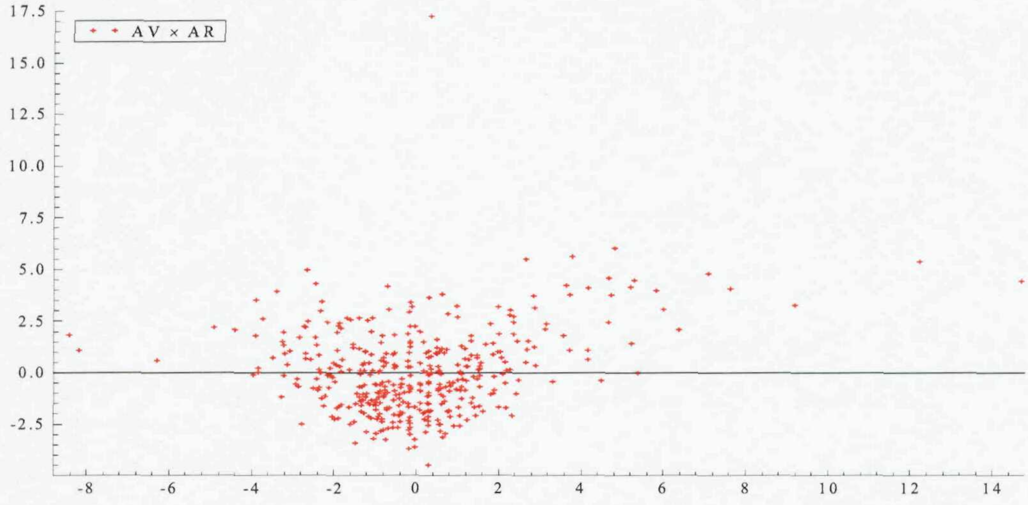


TONGRENTANG

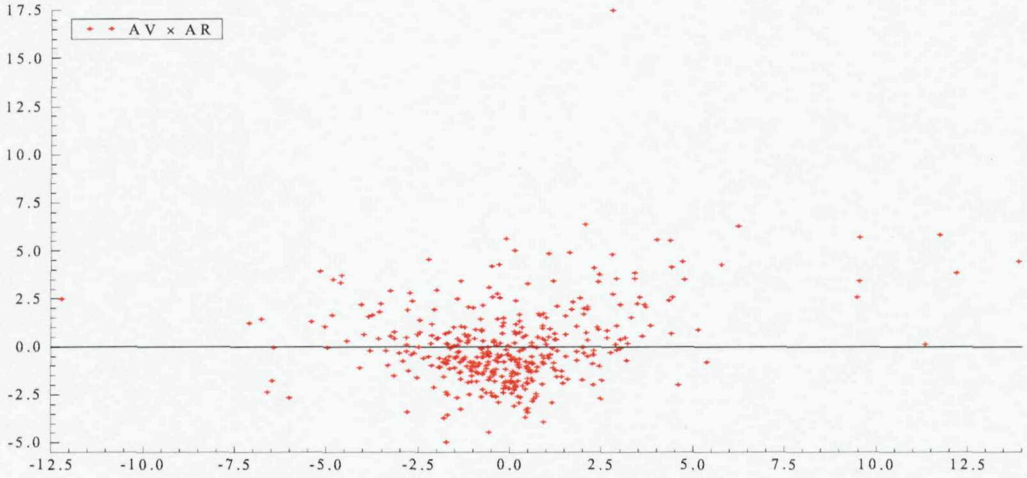


HAIXIN GROUP

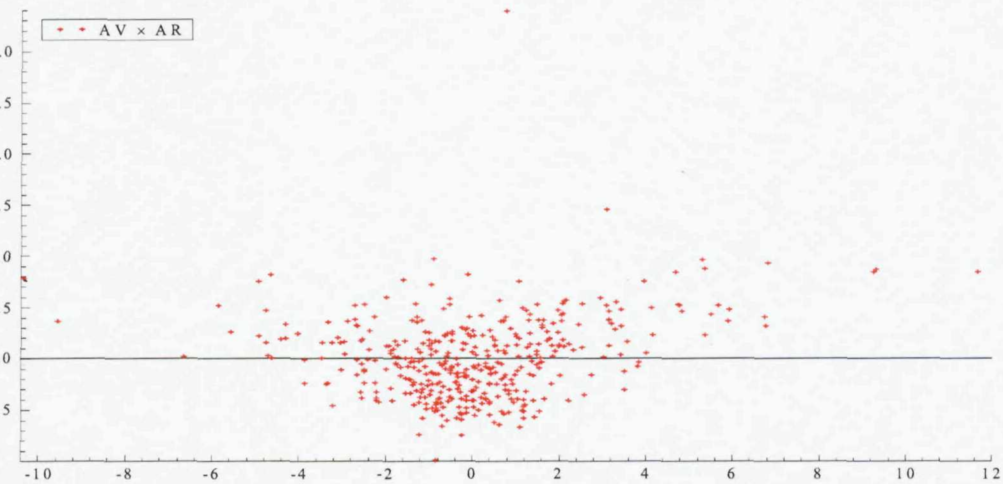
Figure 2.1 (Continued)



SINOPEC CORP



SHENERGY CO



SHANGHAI AUTO

Table 2.3 This table displays the results of the linear Granger causality test of the null hypothesis that there is no causal relation as proposed by Hsio (1981). The following two equations are tested,

$$AR_t = \sum_{i=1}^{m} \alpha_i AR_{t-i} + \sum_{i=1}^{n} \beta_i AV_{t-i} + U_{AR,t},\ t = 1,2,3...,$$

$$AV_t = \sum_{i=1}^{r} \delta_i AR_{t-i} + \sum_{i=1}^{s} \theta_i AV_{t-i} + U_{AV,t},\ t = 1,2,3...,$$

where AV_t and AR_t are adjusted standardized volume and adjusted standardized returns, respectively. (m,n) and (r,s) are two pair numbers chose that denote the number of optimal lags on the adjusted standardized returns and adjusted standardized volume in the above two equations, respectively. FPE $(\bullet,\bullet)$ denotes the corresponding final predictive errors.

	m	n	FPE (m, 0)	FPE (m, n)	F-statistics	s	r	FPE(s, 0)	FPE(s, r)	F-statistics
A SHARE PRICE INDEX[a]	30	4	5.396	5.327*	6.508	8	1	3.283	3.084*	7.856
SHANGHAI AIRPORT	19	1	5.574	5.602	0.004	5	1	2.536	2.484*	10.409
BAOSHAN STEEL	16	1	7.110	7.140	0.286	4	2	2.220	2.129*	20.021
HUANENG POWER	20	1	6.807	6.726*	6.328	3	1	2.577	2.522*	10.752
SH CONTAINER	3	1	20.640	20.706	0.696	10	3	1.977	1.974*	5.824
SINOTRANS DEV	1	1	18.058	17.839*	7.019	6	1	2.702	2.697*	2.932
TONGRENTANG	26	1	6.508	6.527	0.818	4	2	2.126	2.106*	7.880
HAIXIN GROUP	22	14	10.252	9.928*	3.660	6	1	3.457	3.440*	3.876
SINOPEC CORP	19	4	5.093	5.021*	7.920	3	2	2.246	2.197*	12.215
SHENERGY CO	22	7	5.733	5.654*	3.409	3	3	2.311	2.236*	4.839
SHANGHAI AUTO	19	1	5.168	5.145*	3.616	5	2	1.968	1.918*	14.059

* denotes the presence of causal relation.

a: the sample period of A-Share Price Index is from January 2002 to December 2006 and data of ten individual stocks covers the period of January 2002 to September 2003.

Table 2.4 This table displays the results of the modified Baek and Brock test for nonlinear Grange causality. $lx = ly$ denotes the number of lags on the residual series used in the test, $m = 1$ and $e = 1.5$. CS and TVAL denote the difference between the two conditional probabilities and the standardized test statistic in equation (2.12).

	H_0: Volume change does not cause returns		H_0: Stock returns do not cause volume changes	
$lx = ly$	CS	TVAL	CS	TVAL
A SHARE PRICE INDEX[a]				
1	0.0018	0.501	0.0061	2.207*
2	0.0040	0.668	0.0030	1.999*
3	0.0006	0.068	0.0018	1.743*
4	0.0123	1.106	0.0013	2.708*
5	0.0183	1.318	0.0028	1.567*
SHANGHAI AIRPORT				
1	-0.0036	-0.614	-0.0067	-1.296
2	-0.0039	-0.357	-0.0148	-1.764
3	-0.0031	-0.207	-0.0133	-1.039
4	0.0026	0.139	0.0062	0.381
5	-0.0135	-0.552	0.0033	0.173
BAOSHAN STEEL				
1	0.0158	2.390**	0.0140	1.814*
2	0.0109	1.299	0.0271	2.118*
3	0.0224	1.982*	0.0283	1.629*
4	0.0214	1.665*	0.0084	0.362
5	0.0120	0.741	-0.0064	-0.199
HUANENG POWER				
1	-0.0008	-0.0143	-0.0012	-0.206
2	0.0054	0.615	0.0027	0.298
3	0.0016	0.139	0.0143	1.65*
4	-0.0092	-0.663	0.0184	1.223
5	-0.0112	-0.629	0.0081	0.388
SH CONTAINER				
1	0.0013	0.273	-0.0016	-0.431
2	0.0159	2.428**	-0.0055	-0.993
3	0.0122	1.706*	-0.0084	-1.221
4	0.0130	1.615	-0.0094	-1.200
5	0.0114	1.672*	-0.0142	-1.630

* Indicates statistical significant at the 95% level for a one-tailed test.

* *Indicates statistical significant at the 99% level for a one-tailed test.

a: the sample period of A-Share Price Index is from January 2002 to December 2006 and data of ten individual stocks covers the period of January 2002 to September 2003.

Table 2.4 (Continued)

	H_0 : Volume change does not cause returns		H_0 : Stock returns do not cause volume changes	
$lx = ly$	CS	TVAL	CS	TVAL
SINOTRANS DEV				
1	0.0314	1.217	0.0058	1.096
2	-0.0155	-1.313	0.0071	0.876
3	-0.0191	-1.207	0.0025	0.222
4	-0.0121	-0.614	-0.0001	-0.006
5	0.0188	0.892	0.0002	0.013
TONGRENTANG				
1	-0.018	-3.820	-0.0124	-2.434
2	-0.0190	-2.223	-0.0097	-1.053
3	-0.0276	-2.117	-0.0130	-0.964
4	-0.0413	-2.059	-0.0108	-0.585
5	-0.0339	-1.336	-0.0203	-0.858
HAIXIN GROUP				
1	0.0240	3.329**	0.0067	1.206
2	0.0444	4.077**	0.0222	2.406**
3	0.0610	4.262**	0.0307	2.678**
4	0.0577	3.184**	0.0418	2.870**
5	0.0585	2.930**	0.0488	3.056**
SINOPEC CORP				
1	-0.0080	-1.845	0.0040	0.075
2	-0.0144	-2.260	0.0015	0.184
3	-0.0283	-2.044	0.0060	0.580
4	-0.0205	-1.826	0.0026	0.194
5	-0.0194	-1.267	-0.0028	-0.172
SHENERGY CO				
1	0.0058	1.116	-0.0002	-0.037
2	0.0007	0.090	-0.0036	-0.416
3	0.0153	1.421	0.0012	0.094
4	0.0252	1.719*	-0.0032	-0.183
5	0.0258	1.313	-0.0142	-0.709
SHANGHAI AUTO				
1	0.0028	0.472	-0.0024	-0.433
2	-0.0047	-0.554	-0.0065	-0.741
3	-0.0038	-0.377	-0.0116	-0.969
4	-0.0175	-1.468	-0.0033	-0.211
5	-0.0361	-2.236	-0.0030	-0.153

* Indicates statistical significant at the 95% level for a one-tailed test.

* *Indicates statistical significant at the 99% level for a one-tailed test.

Table 2.5 This table displays the results of the modified Baek and Brock test for nonlinear Grange causality. $lx = ly$ denotes the number of lags on the residual series used in the test, $m = 1$ and $e = 1.5$. CS and TVAL denote the difference between the two conditional probabilities and the standardized test statistic in equation (2.12) based on the assumption that the liquid constraint is removed.

	H_0: Volume change does not cause returns		H_0: Stock returns do not cause volume changes	
$lx = ly$	CS	TVAL	CS	TVAL
SHANGHAI AIRPORT				
1	0.0055	2.046*	0.0009	1.634*
2	0.0016	1.800*	0.0010	1.748*
3	0.0014	1.718*	0.0012	1.849*
4	0.0018	1.945*	0.0006	1.275
5	0.0291	1.899*	0.0008	1.544
BAOSHAN STEEL				
1	0.0221	2.467**	0.0034	1.518
2	0.0220	1.937*	0.0020	1.618
3	0.0318	2.334**	0.0019	1.843*
4	0.0270	1.884*	0.0023	1.970*
5	0.0017	1.383	0.0023	1.950*
HUANENG POWER				
1	0.0189	2.088*	0.0047	1.797*
2	0.0116	1.776*	0.0017	1.764*
3	0.0060	1.134	0.0030	1.941*
4	0.0087	1.340	0.0026	1.712*
5	0.0093	1.358	0.0023	1.468
SH CONTAINER				
1	0.0230	2.237*	0.0012	0.424
2	0.0086	2.137*	0.0006	1.093
3	0.0066	2.202*	0.0017	1.129
4	0.0064	2.129*	0.0018	1.156
5	0.0068	2.067*	0.0019	1.145
SINOTRANS DEV				
1	-0.0049	-0.759	0.0011	0.912
2	-0.0075	-0.802	0.0025	1.366
3	0.0018	0.813	0.0023	1.300
4	0.0023	0.834	0.0021	1.179
5	0.0025	0.912	0.0019	1.043

* Indicates statistical significant at the 95% level for a one-tailed test.

* *Indicates statistical significant at the 99% level for a one-tailed test.

Table 2.5 (Continued)

	H_0 : Volume change does not cause returns		H_0 : Stock returns do not cause volume changes	
$lx = ly$	CS	TVAL	CS	TVAL
TONGRENTANG				
1	0.0083	1.657*	0.0043	1.894*
2	0.0635	2.391**	0.0037	1.512
3	0.0509	1.514	0.0019	1.550
4	0.0407	2.910***	0.0042	1.114
5	0.0560	2.937**	0.0027	0.694
HAIXIN GROUP				
1	0.0162	2.564**	0.0423	2.227*
2	0.1623	2.109*	0.0555	2.518**
3	0.0364	2.558**	0.0644	2.827**
4	0.0427	2.690**	0.0214	1.782*
5	0.0542	3.185**	0.0243	1.700*
SINOPEC CORP				
1	0.1000	3.900**	0.0051	0.6301
2	0.0158	1.877*	0.0105	0.9850
3	0.0131	2.319*	0.0183	0.4670
4	0.0191	2.209*	0.0697	0.7450
5	0.0172	2.128*	0.2678	1.494
SHENERGY CO				
1	0.0175	2.526**	0.0059	2.138*
2	0.0303	2.895**	0.0092	2.016*
3	0.0313	2.548**	0.0101	2.017*
4	0.0365	2.581**	0.0124	2.260*
5	0.0307	1.857*	0.0123	2.139*
SHANGHAI AUTO				
1	0.0172	1.868*	0.0038	1.716*
2	0.0220	2.171*	0.0046	1.872*
3	0.0122	1.845*	0.0027	1.757*
4	0.0169	1.187	0.0028	1.867*
5	0.0054	0.757	0.0024	1.709*

* Indicates statistical significant at the 95% level for a one-tailed test.

* *Indicates statistical significant at the 99% level for a one-tailed test.

Figure 3.1 The Autocorrelation Function of the series of daily aggregate trading volume of funds listed on the Shanghai Stock Exchange during the period from 9th June 2000 until 31st December 2004.

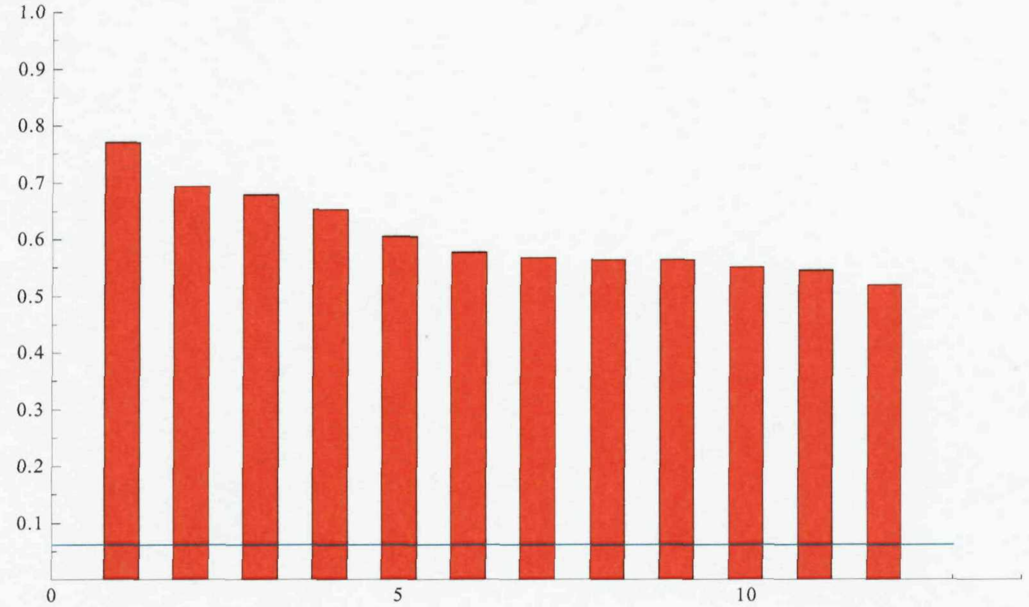


Figure 3.2 The Autocorrelation Function of the series of daily aggregate turnover of Funds listed on the Shanghai Stock Exchange during the period from 9th June 2000 until 31st December 2004.

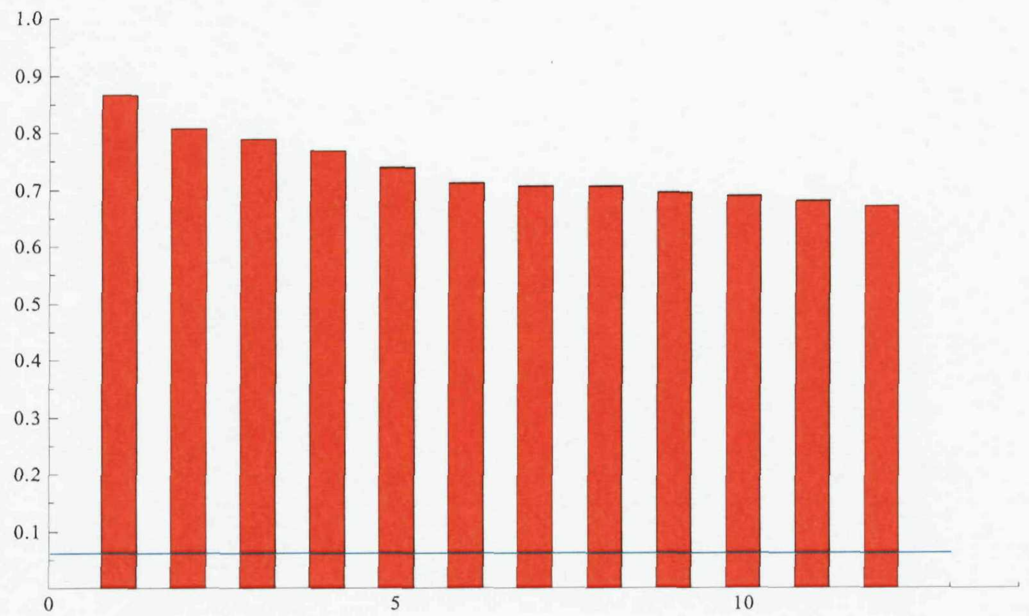


Figure 3.3 Daily returns of Shanghai A-Share Price Index over the period 2nd January 1996 to 31st December 2004.

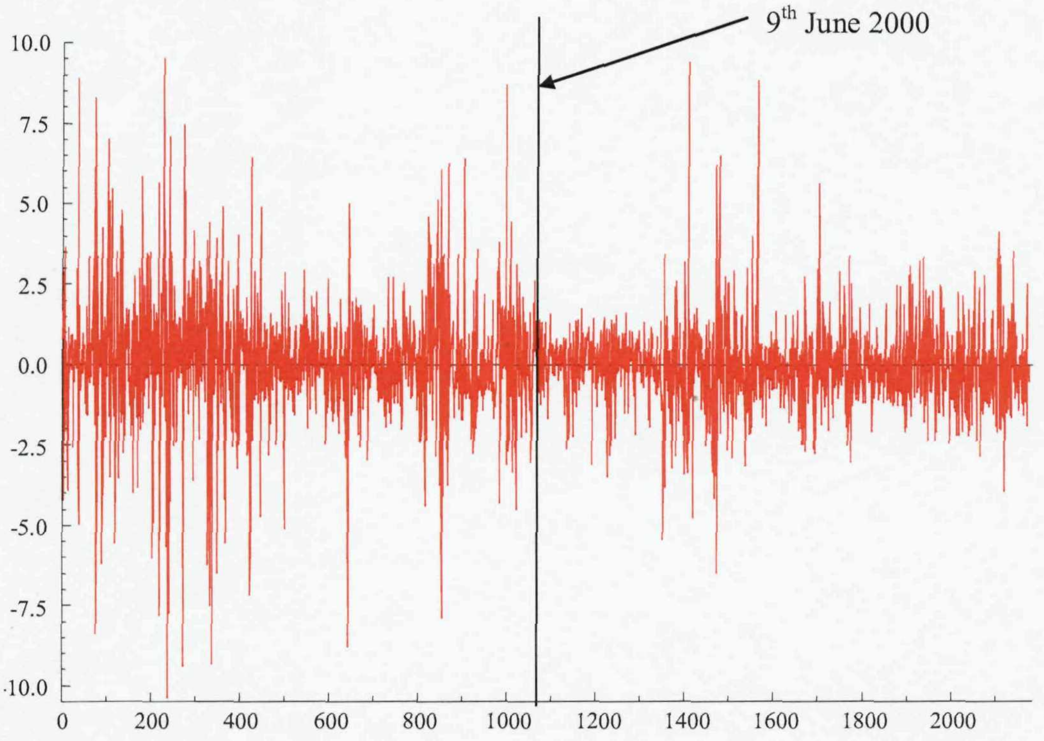


Figure 3.4 The time series plots of closing price of Shanghai A-Share Price Index during the period from 2nd January 1996 to 31st December 2004

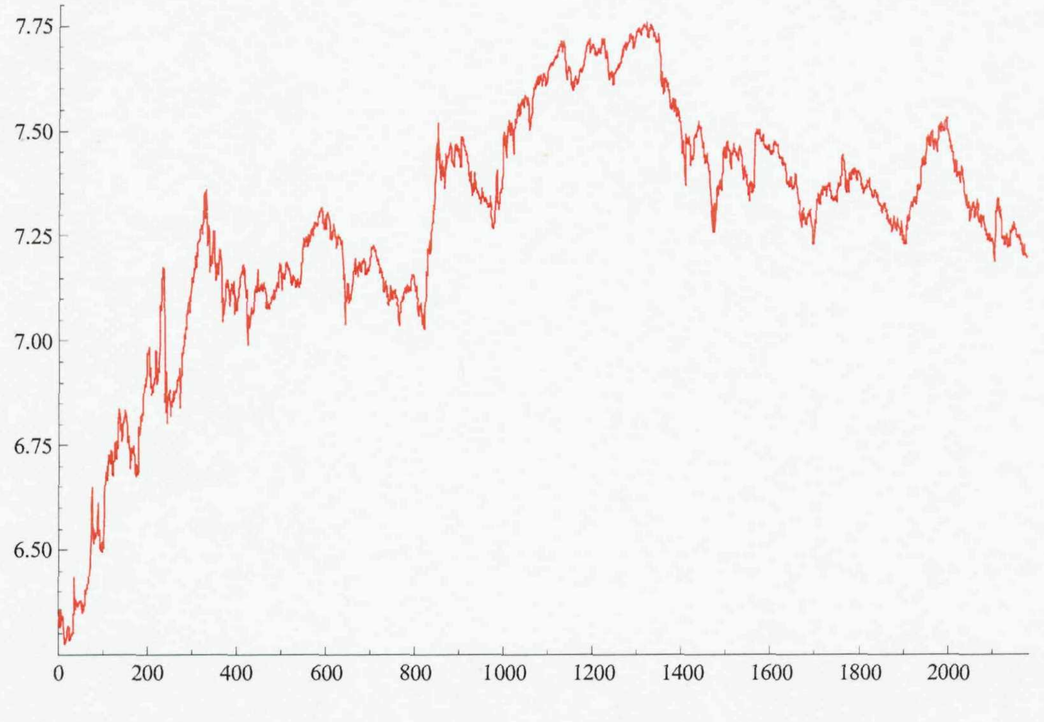


Table 3.1 This table presents time series regressions of daily aggregate trading volume and turnover of listed funds on their own lagged variables for the period 9th June 2000 through 31st December 2004. T-statistics are in parentheses.

Independent variables	Regression I	II	III	IV	V
Panel A	Trading Volume				
Constant	4.3504(11.9)	3.2714(8.67)	2.5194(6.62)	2.2169(5.75)	2.1718(5.54)
Lag 1	0.7715(40.2)	0.5813(19.9)	0.5256(17.9)	0.4991(16.6)	0.4969(16.4)
Lag 2		0.2469(8.44)	0.1147(3.45)	0.1008(3.03)	0.0971(2.89)
Lag 3			0.2272(7.72)	0.1655(4.98)	0.1641(4.91)
Lag 4				0.1182(3.93)	0.1081(3.21)
Lag 5					0.0196(0.65)
R^2	0.595	0.62	0.64	0.645	0.645
F-statistics [p value][a]	[0.0000]	[0.0000]	[0.0004]	[0.3149]	[0.2576]
Panel B	Turnover				
Constant	2.5264(8.82)	1.9250(6.68)	1.500(5.22)	1.3167(4.55)	1.2700(4.34)
Lag 1	0.8668(57.5)	0.6634(22.6)	0.6134(20.8)	0.5882(19.6)	0.5844(19.3)
Lag 2		0.2351(8.01)	0.0914(2.63)	0.0801(2.31)	0.0745(2.13)
Lag 3			0.2160(7.32)	0.1442(4.16)	0.1422(4.09)
Lag 4				0.1180(3.93)	0.0973(2.79)
Lag 5					0.0344(1.14)
R^2	0.751	0.765	0.776	0.779	0.80
F-statistics [p value][a]	[0.0000]	[0.0000]	[0.0002]	[0.3331]	[0.1529]

a. The test for the presence of first-order and second-order autocorrelation in the residuals.

Table 3.2 This table presents the result of the following GARCH (1, 1) model:

$R_t = \omega + \theta_1 R_{t-1} + \theta_2 D_t + \varepsilon_t$

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma D_t$

$D_t = 1$ after 9th June 2000; 0 otherwise

where R_t is the return of A-Share Price Index and D_t is the time dummy variable, and the error term ε_t denotes the unpredictable component of index return with mean zero and the conditional variance h_t. The above model is used to examine the impact of fund trading on the stock prices. The time dummy variable is included in both mean equation and conditional volatility equation. The sample starts 2nd January 1996 and ends 31st December 2004 that amounts to 2177 observations. The estimators are reported and Standard Errors are in parentheses.

	Coefficient	p-value
ω	0.0946(0.0439)**	0.034
θ_1	0.0027(0.0216)	0.899
θ_2	-0.1238(0.05344)**	0.025
α_0	0.2358(0.0690)***	0.004
α_1	0.1670(0.0300)***	0.000
β_1	0.7851(0.0355)***	0.000
γ	-0.1119(0.0453)**	0.023
Log-likelihood	-3828.54	

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

Table 3.3 This table reports the results of the following GARCH (1, 1) model:

$$R_t = \omega + \theta_1 R_{t-1} + \theta_2 V_{t-1} + \varepsilon_t$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma V_{t-1}$$

where R_t is the return of A-Share Price Index and V_{t-1} is the daily aggregate trading volume of funds listed on the Shanghai Stock Exchange at time $t-1$, and the residual ε_t is with mean zero and the conditional variance h_t. And the aggregate daily volume is used as proxy for the daily aggregate fund flow. This model is employed to investigate the effect of fund flow on stock prices during the period of 9th June 2000 to 31st December 2004. Column A shows the results of the above model. Column B and C show the results of the model when the exogenous variable, daily aggregate trading volume, is replaced by the expected daily aggregate trading volume and unexpected daily aggregate trading volume. Standard Errors are in parentheses.

	Column A: Coefficient	Column B: Coefficient	Column C: Coefficient
ω	-1.5040(0.607)***	-2.064(0.7498)***	-0.0274(0.0302)
θ_1	0.0116(0.0298)	0.0146(0.0295)	0.0190(0.0298)
θ_2	0.0774(0.0316)***	0.1067(0.0392)***	0.0110(0.0584)
α_0	0.9188(0.4271)**	0.7863(0.445)*	0.0788(0.0278)***
α_1	0.1257(0.0299)***	0.1242(0.0295)***	0.1133(0.0270)***
β_1	0.8202(0.0394)***	0.8272(0.0370)***	0.8464(0.0321)***
γ	-0.0427(0.0209)**	-0.0362(0.0205)*	-0.1357(0.0400)***
Log-likelihood	-1704.22	-1700.69	-1703.09

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

Table 3.4 This table reports the results of the following GARCH (1, 1) model:

$R_t = \omega + \theta_1 R_{t-1} + \theta_2 T_{t-1} + \varepsilon_t$

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma T_{t-1}$

where R_t is the return of A-Share Price Index and T_{t-1} is the daily aggregate turnover of funds listed on the Shanghai Stock Exchange at time $t-1$, and the residual ε_t is with mean zero and the conditional variance h_t. And the daily aggregate turnover is used as proxy for the daily aggregate fund flow. This model is employed to investigate the effect of fund flow on stock prices during the period of 9th June 2000 to 31st December 2004. Column A shows the results of the above model. Column B and C show the results of the model when the exogenous variable, daily aggregate turnover, is replaced by the expected daily aggregate turnover and unexpected daily aggregate turnover. Standard Errors are in parentheses.

	Column A: Coefficient	Column B: Coefficient	Column C: Coefficient
ω	-1.4298(0.5379)***	-1.8813(0.6077)***	-0.0271(0.0301)
θ_1	0.0105(0.0298)	0.0137(0.0295)	0.0212(0.0300)
θ_2	0.0738(0.0281)***	0.0974(0.0318)***	0.0032(0.0649)
α_0	0.7543(0.3700)**	0.6276(0.3379)*	0.0895(0.0302)***
α_1	0.1264(0.0301)***	0.1255(0.0297)***	0.1231(0.0283)***
β_1	0.8203(0.0396)***	0.8268(0.0368)***	0.8314(0.0340)***
γ	-0.0342(0.0179)*	-0.0279(0.0165)*	-0.2332(0.0649)***
Log-likelihood	-1704.16	-1699.93	-1701.67

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

Table 3.5 This table reports the results of the following GARCH (1, 1) model:

$R_t = \omega + \theta_1 R_{t-1} + \theta_2 V_t + \varepsilon_t$

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma V_t$

where R_t is the return of A-Share Price Index and V_t is the daily aggregate trading volume of funds listed in Shanghai Stock Exchange at time t, and the residual ε_t is with mean zero and the conditional variance h_t. And the aggregate daily volume is used as proxy for the daily aggregate fund flow. This model is employed to investigate the effect of fund flow on stock prices during the period of 9th June 2000 to 31st December 2004. Column A shows the results of the above model. Column B and C show the results of the model when the exogenous variable, daily aggregate trading volume, is replaced by the expected daily aggregate trading volume and unexpected daily aggregate trading volume. Standard Errors are in parentheses.

	Column A: Coefficient	Column B: Coefficient	Column C: Coefficient
ω	-2.7835(0.5970)***	-2.0894(0.7501)***	-0.0305(0.0313)
θ_1	-0.0019(0.0294)	0.0114(0.0300)	-0.0152(0.0308)
θ_2	0.1447(0.0312)***	0.1081(0.0392)***	0.2326(0.0682)***
α_0	0.5487(0.3270)*	0.9074(0.4490)**	0.3219(0.0944)***
α_1	0.1180(0.0281)***	0.1249(0.030)***	0.1548(0.0334)***
β_1	0.8424(0.0331)***	0.8245(0.0380)***	0.6398(0.0694)***
γ	-0.0245(0.0163)	-0.0423(0.0221)*	0.0354(0.1030)***
Log-likelihood	-1689.36	-1701.11	-1691.02

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

Table 3.6 This table reports the results of the following GARCH (1, 1) model:

$R_t = \omega + \theta_1 R_{t-1} + \theta_2 T_t + \varepsilon_t$

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma T_t$

where R_t is the return of A-Share Price Index and T_t is the daily aggregate turnover of funds listed in Shanghai Stock Exchange at time t, and the residual ε_t is with mean zero and the conditional variance h_t. And the daily aggregate turnover is used as proxy for the daily aggregate fund flow. This model is employed to investigate the effect of fund flow on stock prices during the period of 9th June 2000 to 31st December 2004. Column A shows the results of the above model. Column B and C show the results of the model when the exogenous variable, daily aggregate turnover, is replaced by the expected daily aggregate turnover and unexpected daily aggregate turnover. Standard Errors are in parentheses.

	Column A: Coefficient	Column B: Coefficient	Column C: Coefficient
ω	-2.6687(0.5248)***	-1.7743(0.6066)***	-0.0191(0.0307)
θ_1	10.0027(0.0293)	0.0104(0.0300)	-0.0175(0.0304)
θ_2	0.1390(0.0275)***	0.0918(0.0317)***	0.3254(0.0767)***
α_0	0.4735(0.2792)*	0.7276(0.3718)**	0.2181(0.0923)**
α_1	0.1216(0.0286)***	0.1260(0.0298)***	0.1456(0.0303)***
β_1	0.8397(0.0331)***	0.8240(0.0382)***	0.7151(0.7260)***
γ	-0.0205(0.0138)	-0.0330(0.0181)*	0.5607(0.1350)***
Log-likelihood	-1696.70	-1700.98	-1684.91

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

Table 3.7 This table presents the results of regression of return dispersion on extreme market movements.

$Df_t = \mu + \gamma_1 D_t^L + \gamma_2 D_t^U + \varepsilon_t$

where Df_t is return dispersion, and D_t^L =1, if the market index return on time t lies in the 1% (5%) lower tail of the return distribution, 0, otherwise; D_t^U =1, if the market index return on time t lies in the 1% (5%) upper tail of the return distribution, 0, otherwise. Standard Errors are in parentheses.

	Market index return in extreme 1% lower and upper tail of the return distribution	Market index return in extreme 5% lower and upper tail of the return distribution
μ	0.5132(0.0339)***	0.4070(0.0341)***
γ_1	3.1585(0.3376)***	1.4454(0.1488)***
γ_2	2.2715(0.3376)***	1.7680(0.1488)***
R^2	0.1070	0.1693
F-test (2,1098)	65.78[0.000]***	112[0.000]***

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

Table 4.1 This table represents the results of the following GARCH family models:

$r_t = \mu + \varepsilon_t$

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D$ (4.4)

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \delta_1 D + \delta_2 \sigma_{C,ml,t-1}^2 + \delta_3 \sigma_{C,II,t-1}^2$ (4.9)

$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \kappa IV_{t-1}$ (4.12)

where r_t is the excess return of Baoshan Steel at time t calculated with risk free return, ε_t is the error term with mean μ and variance h_t, D is the time dummy variable which is equal to one after 22nd August 2005 and zero otherwise, $\sigma_{C,ml,t-1}^2$ and $\sigma_{C,II,t-1}^2$ are the cross-sectional market and industry volatility at time $t-1$, and IV_{t-1} represents the implied volatility of warrant on Baoshan Steel calculated from the dilution-adjusted Black-Scholes model at time $t-1$. Column A, B and C show the empirical results of specification (4.4), (4.9) and (4.12), respectively. Numbers in parentheses denote asymptotic t-statistics.

	Column A	Column B	Column C
μ	-0.0854	-0.0066	0.0009
	(-1.29)	(-0.11)	(0.773)
α_0	0.8505***	0.7698	0[b]
	(2.66)	(1.1)	(0.146)
α_1	0.0814*	0.0339***	-0.0430***
	(1.86)	(32.9)	(-4.93)
β_1	0.7302***	-0.0338***	0.1034*
	(16.3)	(-32.5)	(1.92)
δ_1	-0.5105**	-0.9055	
	(-2.00)	(-1.48)	
δ_2		0.2997[a]	
		(1.61)	
δ_3		0.9653***	
		(4.19)	
κ			0.0231***
			(5.52)
Log-likelihood	-1189.05	-807.38	-559.80

* denotes significance at the 10% level
** denotes significance at the 5% level
*** denotes significance at the 1% level
a: It is marginal significant at 10% level.
b: 6.39897e-008

Table 4.2 This table displays the results of information content regressions:

$RV_t = \theta_0 + \theta_1 IV_t + \eta_t$ (4.13)

$RV_t = \theta_0 + \theta_1 IV_t + \theta_2 HV_{t-1} + \eta_t$ (4.15)

where RV_t is the realized volatility of Baoshan Steel over the remaining life of warrant contract, IV_t represents the implied volatility of warrant on Baoshan Steel calculated from the dilution-adjusted Black-Scholes model at time t, HV_t is historical volatility with a moving window of 20 trading days at time t and η_t is the error term. We choose the past implied volatility as the instrument variable to correct for error-in-variable. And a two-stage procedure is adopted to estimate the regression above. OLS estimates of specification (4.13) and (4.15) are shown in the table below. In addition, Hansen-White variance-covariance matrix is employed to consider the dependence of the error terms due to the use of overlapping observations. Numbers in parentheses denote asymptotic t-statistics.

θ_0	θ_1	θ_2	R^2
0.0801***	0.6755***		6.15%
(4.45)	(3.43)		
0.0155***		0.2042***	1.8%
(20.2)		(3.67)	
0.0131***	0.4667***	0.0938*	8.22%
(14.1)	(4.14)	(1.84)	

* denotes significance at the 10% level

** denotes significance at the 5% level

*** denotes significance at the 1% level

References

Akaike, H., 1969, Statistical predicator indentification, Annals of the Institute of Statistical Mathematics 21, P203-217.

Akaike, H., 1974, A new look relationship at the statistical model identification, IEEE Transactions on Automatic Control 19, P716-723.

Alkeback, P. and N. Hagelin, 1998, The impact of warrant introductions on the underlying stocks, with a comparison to stock options, Journal of Futures Markets 18(3), P307-328.

Andersen, T. and T. Bollerslev, 1998, answering the sceptics: Yes, standard volatility models do provide accurate forecasts, International Economic Review 39(4), P885-905.

Antoniou, A., and P. Holmes, 1995, Future trading, information and spot price volatility: evidence for the FTSE-100 Stock Index Futures contract using GARCH, Journal of Banking and Finance 19, P117-129.

Back, K., 1993, Asymmetric information and options, Review of Financial Studies 6(3), P435-472.

Baek, E. and W. Brock, 1992, A causal relationship between stock returns and volume, Working paper, Iowa state University and University of Wisconsin, Madison.

Balduzzi, P., Kallal, H. and F. Longin, 1996, Minimal returns and the breakdown of the price-volume relation, Economics Letters 50, P265-269.

Beltratti, A. and B. Bortolotti, 2006, The Nontradable share reform in the Chinese Stock Market, working paper, Bocconi University.

Bergman, Y., Grundy, B., and Z. Wiener, 1996, General properties of options, Journal of Finance 51, P1573-1610.

Blair, B.J., Poon, S.H. and S.J. Taylor, 2001, Forecasting S&P 100 volatility: the incremental information content of implied volatilities and high-frequency index returns, Journal of Econometrics 105, P5-26.

Blume, L., Easley, D. and M. O'Hara, 1994, Market statistic and technical analysis: the role of volume, Journal of Finance 49 (1), 153-181.

Bohl, M.T. and J. Brzeszczynski, 2005, Do institutional investors destabilize stock prices? Evidence from an emerging market, working paper, Centre for economic reform and transformation, Heriot-Watt University.

Bollen, N., 1998, A note on the impact of options on stock return volatility, Journal of Banking and Finance 22, P1181-1191.

Bollerslev, T. 1986, Generalised autoregressive conditional heteroskedasticity, Journal of Econometrics 31, P307-327.

Bollerslev, T., Chou, R.Y., and K.F. Kroner, 1992, ARCH modelling in finance: a review of the theory and empirical evidence, Journal of Econometrics 52, P5-59.

Busse, J., 1999, Volatility timing in mutual funds: evidence from daily returns, The Review of Financial Studies 12, P1009-1041.

Campbell, J., Grossman, S. and J. Wang, 1993, Trading volume and series correlations in stock returns, Quarterly Journal of Economics 108, P905-939.

Campbell, J., Lettau, M., Malkiel, B. and Y. Xu, 2001, Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, Journal of Finance 56(1), P1-43.

Canina, L. and S. Figlewski, 1993, The information content of implied volatility, Review of Financial Studies 6(3), P659-681.

Chan, L.K.C. and J. Lakonishok, 1993, Institutional trades and intra-day stock price behaviour, Journal of Financial Economics 33, P173-199.

Chan, L.K.C. and J. Lakonishok, 1995, The behaviour of stock prices around institutional trades, Journal of Finance 50 (4), P1147-1174.

Chan, Y.C. and K.C.J.Wei, 2001, Price and volume effects associated with derivative warrant issuance on the Stock Exchange of Hong Kong, Journal of Banking and Finance 25, P1401-1426.

Chang, E.C., Cheng J.W. and A. Khorana, 2000, An examination of herd behaviour in equity markets: An international perspective, Journal of Banking and Finance 24(10), P1651-1699.

Chen, Z. and P. Xiong, 2001, Discounts on illiquid stocks: evidence from China, working paper, the China Center for Economic Research, Beijing University.

Chen, M., Firth, M. and O. M. Rui, 2001, The dynamic relation between stock returns, trading volume, and volatility, The Financial Review 38, P153-174.

Christensen, B.J. and N.R. Prabhala, 1998, The relation between implied and realized volatility, Journal of Financial Economics 50, P125-150.

Christie, J.Y. and R.D. Huang, 1995, Following the pied piper: Do individual returns herd around the market? Financial Analysts Journal, July-August, P31-37.

Clark, P., 1973, A subordinated stochastic process model with finite variances for speculative prices, Econometrica 41, P135-155.

Cohen, R.B., Paul A.G. and T. Vuolteenaho, 2002, Who underreacts to cash-flow news? Evidence from trading between individuals and institutions, Journal of Financial Economics, 66, P409-462.

Connor, G., Korajczyk, R.A. and O. Linton, 2006, The common and specific components of dynamic volatility, Journal of Econometrics 132, P231-255.

Conrad, J., 1989, The price effect of options introduction, Journal of Finance 44(2), P487-498.

Copeland, L. and B.Q. Zhang, 2003, Volatility and volume in Chinese Stock Market, Journal of Chinese Economic and Business Studies 1(3), P287-300.

Crouhy, M. and D. Galai, 1991, Common errors in the valuation of warrants and options on firms with warrants, Financial Analysts Journal, September-October, P89-90.

Darrat A.F., Zhong, M and L. T.W. Cheng, 2006, Trading without public news: Another look at the intraday volume-volatility stock relations, working paper, UQ Business School, The University of Queensland.

Day, T.E. and C.M. Lewis, 1992, stock market volatility and the information content of stock index options, Journal of Econometrics 52, P267-287.

De Jong, F., Nijman, Th.E. and A., Roell, 1995, A comparison of the cost of trading French shares on the Paris Bourse and on SEAQ international, European Economic Review, 39, P1277-1301.

De Jong, F., Nijman, Th.E. and A., Roell, 1996, Price effects of trading and components of the bid-ask spread on the Paris Bourse, Journal of Empirical Finance 3, P193-213.

Delong, J., Shleifer, A., Summers, L. and B. Waldmann, 1990, Positive feedback investment strategies and destabilizing speculation, Journal of Finance 45(2), 379-395.

Demirer, R. and A.M. Kutan, 2004, Does herding behaviour exist in Chinese Stock Markets? , working paper, Southern Illinois University Edwardsville.

Dennis, P. and D. Strickland, 2002, Who blinks in volatile markets, individuals or institutions?, Journal of Finance 57(5), P1923-1949.

Detemple, J. and L. Selden, 1991, A general equilibrium analysis of option and stock market interactions, International Economic Review 32(2), P279-303.

Dridi, R. and L., Germain, 2000, Bullish-Bearish strategies of trading: A nonlinear equilibrium, working paper, Toulouse Business School.

Edelen, R.M. and J.B. Warner, 2001, Aggregate price effects of institutional trading: a study of mutual fund flow and market returns, Journal of Financial Economics 59, P195-220.

Engle, R.F. and T. Bollerslev, 1986, Modelling the persistence of.conditional variances, Econometric Review 5, P1-50.

Engle, R.F., 1982, Autoregressive conditional heteroscdasticity wit estimates of the variance of United Kingdom inflation, Econometrica 50, P987-1008.

Epps, T. and M. Epps, 1976, The stochastic dependence of security price changes and transaction volumes: Implications for the mixture of distributions hypothesis, Econometrica 44, P305-321.

Fama, E. F., 1965, The behaviour of stock market prices, Journal of Business 38, P34-105.

Faugere, C. and H.A. Shawky, 2003, Volatility and Institutional investor holdings in a declining market: A study of Nasdaq market during the year 2000, working paper, Center for institutional investment management, University at Albany, SUNY.

Fedenia, M., and T. Gammatikos, 1992, Options trading and the bid-ask spread of the underlying stocks, Journal of Business 65, P335-351.

Fleming, J., 1998, The quality of market volatility forecasts implied by S&P 100 index option prices, Journal of Empirical Finance 5, P317-345.

French, S., Schwert, W. and R. Stambaugh, 1987, Expected stock returns and volatility, Journal of Financial Economics 19, P3-29.

Freund, S., McCann, P.D. and G.P. Webb, 1994, A regression analysis of the effects of option introduction on stock variance, Journal of Derivatives 1(3), P25-38.

Gabaix, X., Gopikerishnan P., Plerou, V. and H. E. Stanley, 2006, Institutional investors and stock market volatility, Quarterly Journal of Economics 121(2), P461-504.

Galai, D. and M.I. Schneller, 1978, Pricing of warrants and the value of the firm, Journal of Finance 33(5), P1333-1342.

Gallant, A. R., Rossi, P.E. and G. Tauchen, 1992, Stock prices and volume, Review of Financial Studies 5, P199-242.

Geweke, J., Meese, R. and W. Dent, 1983, Comparing alternative tests of causality in temporal systems: Analytic results and experimental evidence, Journal of Econometrics 21, P161-194.

Goetzmann, W.N. and M. Massa, 2003, Index funds and stock market growth, Journal of Business 76(1), P1-28.

Granger, C., 1969, Investigating causal relations by econometric models and cross-spectral methods, Econometrica 37, P424-438.

Grossman, S., 1988, An analysis of the implication for stock and return price discovery in stock, future, and option markets, Journal of Futures Markets 16, P353-387.

Hansen, L.P., 1982, Large sample properties of generalized method of moments estimators, Econometrica 50, P1029-1054.

Harris, L., 1989, S&P 500 cash stock price volatilities, Journal of Finance 44, P1155-1175.

Hart, O. and D. Kreps, 1986, Price destabilizing speculation, Journal of Political Economy 94, P927-952.

Hasbrouck, J., 1993, Assessing the quality of a security market: A new approach to transaction cost measurement, Review of Financial Studies 4, P571-595.

Hausman, J.A., Lo, A.W. and A.C. McKinaly, 1992, An ordered probit analysis of transaction stock prices, Journal of Financial Economics 31, P319-379.

He, H. and J. Wang, 1995, Differential informational and dynamic behaviour of stock trading volume, Review of Financial Studies 8(3), P919-972.

Hernandez-Trillo, F., 1999, Financial derivatives introduction and stock return volatility in an emerging market without clearinghouse: the Mexican experience, Journal of Empirical Finance 6, P153-176.

Hiemstra, C., and J. Jones, 1993, Monte Carlo results for a modified version of the Baek and Brock nonlinear Granger causality test, Working paper, University of Strathclyde and Securities and Exchange Commission.

Hiemstra, C., and J. Jones, 1994, Testing for linear and nonlinear Granger Causality in the stock price-volume relation, Journal of Finance 50(5), P1639-1664.

Holthausen, R., Leftwich, R. and D. Mayers, 1987, The effect of large block transactions on security prices: A cross-sectional analysis, Journal of Financial Economics 19, P237-268.

Hong, Y., Liu, Y. and S. Wang, 2006, Granger Causality in risk and detection of extreme risk spillover between financial markets, working paper, Cornell University and Xiamen University.

Hsiao, C., 1981, Autoregressive modelling and money-income causal detection, Journal of Monetary Economics 46, P85-106.

Hull, J.C. and A. White, 1987, The pricing of options on assets with stochastic volatilities, Journal of Finance 42(2), P281-300.

Hwang, S. and M. Salmon, 2004, Market stress and herding, Journal of Empirical Finance 11, P585-616.

Hwang, S. and S.E. Satchell, 2000, Market risk and the concept of fundamental volatility: measuring volatility across asset and derivative markets and testing for the impact of derivatives markets on financial markets, Journal of Banking and Finance 24, P759-785.

Hwang, S. and S.E. Satchell, 2001, GARCH model with cross-sectional volatility: GARCHX models, Financial Econometric Research Centre working paper, City University Business School.

Hwang, S. and S.E. Satchell, 2004, Properties of cross-sectional volatility, Financial Econometric Research Centre working paper, City University Business School.

Inoue, T., 2005, Reform of China's split-structure takes shape, Nomura Capital Market Review 8(3), P1-20.

Jennings, R. and L. Starks, 1986, Earning announcements, stock price adjustment and the experience of option markets, Journal of Finance 41(1), P107-125.

Jennings. R., Starks, L. and J. Fellingham, 1981, An equilibrium model of asset trading with sequential information arrival, Journal of Finance 36, P143-161.

John, K., Koticha, A. and M. Subrahmanyam, 1993, The micro-structure of option markets: informed trading, liquidity, volatility and efficiency, working paper, New York University.

Jones, C.S., 2001, Extracting factors from hetetroskedastic asset return, Journal of Financial Economics 62, P293-325.

Jong, C., Koedijk, K.G. and C.R. Schnitzlein, 2004, Stock market quality in the presence of a traded option, working paper, College of Business and Public Administration of University Central Florida.

Jorion, P., 1995, Predicting volatility in the foreign exchange market, Journal of Finance 50(2), P507-528.

Kahl, M., Liu, J., and F.A. Longstaff, 2003, Paper millionaires: how valuable is stock to a stockholder who is restricted from selling it?, Journal of Financial Economics 67, P385-410.

Karpoff, J. M., 1987, The relation between price changes and trading volume: A survey, Journal of Financial and Quantitative Analysis 22, P109-126

Kempf, A. and O., Korn, 1999, Market Depth and Order Size, Journal of Financial Markets 2, P29-48.

Kim, M., Nelson, C. and R. Startz, 1991, Mean reversion in stock prices? A reappraisal of the empirical evidence, Review of Economic Studies 58, P515-528.

Kumar, R., Sarin, A. and K. Shastri, 1998, The impact of options trading on the market quality of the underlying security: an empirical analysis, Journal of Finance 53(2), P717-732.

Lakonishok, J. and S. Smidt, 1989, Past price changes and current trading volume, The Journal of Portfolio Management 15, P18-24.

Lakonishok, J., Shleifer, A. and R.W. Vishny, 1992, The impact of institutional trading on stock prices, Journal of Financial Economics 32, P23-43.

Lamoureux, C., 1991, Option listing does not affect the variance of the underlying stock: a cautionary tale, working paper, Washington University in St.Louis.

Lamoureux, C.G.. and W.D. Lastrapes, 1993, Forecasting stock-return variance: toward an understanding of stochastic implied volatilities, Review of Financial Studies 6(2), P293-326.

Lauterbach, B. and P. Schultz, 1990, Pricing warrant: an empirical study of the Black-Scholes models and its alternatives, Journal of Finance 45(4), P1181-1209.

Lipson, M. and A. Puckett, 2005, Volatile markets and institutional trading, working paper, Terry college of Business of University of Georgia.

Llorente, G., Michaely, R., Saar, G. and J. Wang, 2002, Dynamic volume-return relation of individual stocks, Review of Financial Studies 15(4), P1005-1047.

Long, D. M., Payne, J.D. and C. Feng, 1999, Information transmission in the Shanghai equity market, The Journal of Financial Research 22, P29-45.

Longstaff, F. 1990, Pricing options with extendible maturities: analysis and applications, Journal of Finance 34, P369-382.

Longstaff, F. A., 2001, Optimal portfolio choice and the valuation of illiquid securities, Review of financial studies 14(2), P407-431.

Luo, D., 2003, Market volatility and mutual fund cash flows, working paper, Yale International Center for Finance.

Marsh, T. A. and N. Wagner, 2003, Return-volume dependence and extremes in international equity markets, working paper, Haas School of Business, UC Berkeley.

Mayhew, S. and V. Mihov, 2000, Another look at option listing effects, working paper, Terry college of Business of University of Georgia.

Mazouz, K., 2004, The effect of CBOE option listing on the volatility of NYSE traded stocks: a time-varying variance approach, Journal of Empirical Finance 11, P695-P708.

Mookerjee, R. and Q. Yu, 1999, An empirical analysis of the equity markets in China, Review of Financial Economics 8, and P41-60.

Nofsinger, J. and R. Sias, 1999, Herding and feedback trading by institutional and individual investors, Journal of Finance 54, P2263-2295.

Pring, M. J., 1991, Technical analysis explained, 3rd ed. McGraw-Hill, New York.

Ratner, M. and R.P.C. Leal, 2001, Stock returns and trading volume: evidence form the emerging markets of Latin America and Asia, Journal of Emerging Markets 6, P5-22

Saatcioglu, K. and L. Starks, 1998, The stock price-volume relationship in emerging stock markets: the case of Latin America, International Journal of Forecasting 14, P215-225.

Sias, R. and L.T. Starks, 1997, Return autocorrelation and institutional investors, Journal of Financial Economics 46, P103-131.

Silber, W.L., 1991, Discounts on restricted stock: the impact of illiquidity on stock prices, Financial Analysts Journal, July-August, and P60-64.

Silvapulle. P. and J. Choi, 1999, Testing for linear and nonlinear Granger Causality in the Stock Price-Volume relation: Korean Evidence, Quarterly Review of Economics and Finance 39, P59-76.

Skinner, D., 1989, Options markets and stock return volatility, Journal of Financial Economics 23, P61-78.

Smirlock, M. and L. T. Starks, 1985, A further examination of stock price changes and transaction volume, Journal of Financial Research 8, 217-225.

Smirlock, M. and L. T. Starks, 1988, An empirical analysis of the stock price-volume relationship, Journal of Banking and Finance 12(1), P31-41.

Veld, C., 2000, Warrant pricing: a review of empirical research, working paper, Tilburg University.

Wang, J., 1994, A model of competitive stock trading volume, Journal of Political Economy 102(1), P127-168.

Warther, V.A., 1995, Aggregate mutual fund flows and security returns, Journal of Financial Economics 39, P209-235.

Wermers, R., 1999, Mutual fund herding and the impact on stock prices, Journal of Finance 54, P581-622.

Wu, R.T., 2001, An empirical study of the effect of price limits on the Shanghai A stock market, unpublished paper, Economic department of University of Southampton.

Wu, W.X. and Y.X. Wang, 2003, Investment with restricted stock and the value of information, working paper, Institution of applied mathematics, AMSS, Chinese Academy of Sciences.

Xu, C.K., 2000, The microstructure of the Chinese stock market, China Economic Review, 11, P79-97.

Xu, X.Z. and S.J. Taylor, 1995, Conditional volatility and the informational efficiency of the PHLX currency options market, Journal of Banking and Finance 19, P803-821.