Daily Analysis of Institutional and Individual Trading and Stock Returns

Evidence from China

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgments), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Qiang Lai

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Abstract

This dissertation examines the impact of institutional (and individual) trading on stock prices in China. Previous literature suggests three alternative hypotheses for this impact: price pressure, informed trading, and momentum trading, but has so far not been able to distinguish between them. Using a unique dataset that contains detailed daily institutional and individual ownership information for all Shanghai Stock Exchange stocks in China, I am able to examine the important relation between daily aggregate institutional (individual) trading and past, contemporaneous, and future stock returns at a daily level. I find strong evidence of price pressure, informed trading, and momentum trading of institutional investors. These findings have important implications for the efficiency of the financial market.

Chapter1

Introduction

The Chinese stock market is one of the fastest growing markets in the world, and is thus becoming an increasingly important market for investors. In particular, institutional ownership and institutional trading activity in China have dramatically increased over the last decade. The number of institutional accounts has nearly doubled, increasing from 2.57 million in 2000 to 4.86 million in 2008, while the percentage of institutional ownership of the total tradable shares has increased from 30.13% in 2005 to 54.62% in 2008[1]. Institutional investors have become a major participant in the Chinese stock market.

The increased level of institutional ownership and institutional trading activity raises important questions for both academics and practitioners concerning the impact of institutional trading on stock prices. This impact could have either positive or negative implications on the efficiency of the Chinese stock market. Generally, there are three main hypotheses that address this impact and its implications. First, recent studies show that substantial institutional trades have a large contemporaneous price impact (Chan and Lakonishok, 1993, 1995; Keim and Madhavan, 1996), and large investors' trading can affect prices (Chiyachantana, Jain, Jiang, and Wood, 2004). The price impact induced by institutional trading may drive prices away from their fundamentals. This so called price pressure hypothesis implies that trading by institutions contemporaneously affects stock prices, because institutional trades require price concessions (Stoll, 1978). Second, institutions are often considered to be informed traders (Chakravarty, 2001; Sias and Starks, 1997), which allows them to time their trades and profit from uninformed investors. This so called informed trading hypothesis suggests that institutions have information that allows them to predict future price movements (Chakravarty, 2001)[2]. Third, institutions might follow momentum trading strategy which can cause prices to deviate from their fundamentals (DeLong, Shleifer, Summers,

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[1] China Securities Registration and Settlement Statistical Yearbook 2008 (from SD&C).
[2] Informed trading can increas informational efficiency by allowing prices to reflect more information about fundamentals (Chordia, Roll, and Subrahmanyam, 2008) or it can reduce market liquidity by pushing uninformed investors away from the market.

and Waldmann, 1990). Furthermore, momentum trading can induce autocorrelation in stock returns and increase the volatility of the market (Koutmos and Saidi, 2001).

Although previous literature shows that institutional trading has an impact on stock prices, it has not been able to disentangle these three hypotheses. For example, although the positive relation between quarterly changes in institutional ownership and the same quarter return is well documented (Grinblatt, Titman, and Wermers, 1995; Wermers, 1999, 2000; Nofsinger and Sias, 1999; and Bennett, Sias, and Starks, 2003), the source of this relation is not clear. It could be due to price pressure, informed trading, and intraquarter momentum trading of institutional investors (Sias, Starks, and Titman, 2006). The high frequency institutional trading data necessary to disentangle these three hypotheses is difficult to obtain. Publicly available databases in particular do not identify institutional trades. For this reason, the previous literature has mainly relied on quarterly or annual changes in institutional holdings data to infer institutional trading[3].

Several recent studies attempt to use proprietary datasets (e.g., Griffin, Harris, and Topaloglu, 2003) to infer high frequency institutional trading. However, the use of these datasets has shortcomings. First, the sample sizes are typically restricted and do not reflect the aggregate daily institutional trading. For example, the dataset of Lee, Li, and Wang (2009) contains only 180 stocks out of 860, while Ng and Wu's (2007) sample stocks only accounts for 32% of the total stock turnover. Second, proprietary data may be subject to selection bias if the data is from a single discount brokerage firm[4]. Therefore, only the combination of the high frequency and detailed aggregate trading data can offer a clear picture of the institutional trading pattern and provide strong evidence of price pressure, informed trading, and momentum trading of institutional investors.

In addition, most studies focus on developed markets, and very little research has focused on emerging markets, such as the Chinese stock market, which is very different from others in several respects. First, only one third of shares in the Chinese stock market are tradable, which is much less than in other markets. Thus, institutional trading is likely to have an impact on stock prices (Mei, Scheinkman, and Xiong, 2004). Second,

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[3] Boehmer and Kelly (2009) find a statistically insignificant correlation (0.04) between actual daily institutional trading using the NYSE's Consolidated Audit Trail Data (CAUD) and trading inferred from changes in 13F holdings (quarterly) during the period from 2000 to 2004.

[4] For example, Odean (1999) employs 10,000 customer accounts from a large U.S. brokerage firm.

the regulatory framework for the stock market is not yet fully developed (Hu, 1999). It is interesting to examine whether the trading behaviour of institutions in a less regulated developing market is different from that of institutions in the well regulated developed markets.

The main contribution of this dissertation is to distinguish between the three important hypotheses: price pressure, informed trading, and momentum trading of institutional investors, and test them directly. In contrast to the previous literature, using a unique dataset that contains detailed daily record of institutional ownership for all the Shanghai Stock Exchange (SSE) stocks, I am able to examine the importance of daily institutional trading in: (1) moving contemporaneous prices, (2) predicting future price movements, and (3) following past stock returns movements. In addition to institutional trading, I also have data on daily individual ownership, which allows me to examine whether individual trading has the same impact on stock prices.

The results of this dissertation can be summarised as follows. First, I find strong evidence for the price pressure effect, there is a strong positive contemporaneous relation between changes in institutional ownership and stock returns at a daily level. Intense institutional trading has a significant impact on stock prices and the price impact is highly economically significant (3.11% per day or 778% per annum[5]). Second, I find a permanent price impact asymmetry between institutional buys and sells. That is, prices go up on buys but down on sells, they remain high after buys, but revert after sells[6]. This pattern suggests that institutions are informed traders in buying decisions but not in selling decisions. The most intensely bought stocks outperform those the most intensely sold stocks by 3.23% 20 days after institutional trading. Furthermore, the Capital Asset Pricing Model (CAPM) test confirms that intensely bought stocks earn significant positive risk-adjusted abnormal returns one month after buying, whereas intensely sold stocks earn insignificant abnormal returns after one month selling. Third, institutions are short-term momentum traders for buying but not for selling. Fourth, the robustness test confirms that institutions engage in herding and/or order splitting.

The relation between individual trading and stock returns shows patterns that are essentially the opposite to those of institutions. First, there is a strong negative contemporaneous relation between changes in individual ownership and stock returns at

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[5] This is the overall price impact which includes both buys and sells impact.
[6] Chan and Lakonishok (1993) and Chan and Lakonishok (1995) document the similar results.

a daily frequency. That is, prices increase when individual sell shares but decrease when they buy shares. Second, I find that individual selling activity is negatively correlated with future returns, suggesting poor performance of individual investors. Third, individuals are contrarian traders for selling but not for buying. These reverse findings are due to the fact that individuals trade with institutions by taking the opposite position, and the correlation between the most intensely bought and sold stocks by institutions and individuals is -0.88.

The implications of this dissertation are as follows. First, the price impact induced by institutional trading increases institutions' total trading cost, i.e. higher price impact costs as well as the volatility of the financial market. Furthermore, institutional trading pushes prices away from their fundamentals, which destabilises the financial market, and reduces its efficiency. Second, the finding that institutions are informed traders is particularly important for regulators and exchange officials concerned with promoting the transparency of information. Third, momentum trading by institutions might also cause stock prices to deviate from their fundamental values, which destabilises the financial market and reduces its efficiency (DeLong et al., 1990). Finally, if individual investors suffer losses from trading with institutions, individual investors should let institutions manage their fund and trade on their behalf. Alternatively, individual investors can profit by mimicking institutional trading.

The rest of the dissertation is organized as follows. Chapter 2 discusses the literature that studies the price pressure, informed trading, and momentum trading of institutional investors. Chapter 3 provides an overview of the China stock market, institutional investors and the Shanghai Stock Exchange, and describes the Topview dataset. Chapter 4 discusses the methodology. Chapter 5 presents the results of the daily relation between institutional and individual trading and contemporaneous, future, and past returns. Finally, Chapter 6 offers conclusion.

Chapter 2

Literature Review

This literature review is divided into two parts, the first part discusses the studies on price pressure, informed trading, and momentum trading of institutional investors, and the second part focuses on the relation between individual trading and stock returns.

2.1 The relation between institutional trading and stock returns

There is an extensive and growing literature on the behaviour of institutional trading and stock returns. For example, many studies have examined the returns on the portfolios that mutual fund report quarterly (e.g. Daniel, Grinblatt, Timan, and Wermers, 1997; Wermers, 2000). Some examine institutional preferences and find that institutions prefer large, liquid stocks and changes in those preferences over time (Gompers and Metrick, 2001; Bennett et al., 2003). Moreover, researchers find that institutions tend to follow past prices movements (Grinblatt et al., 1995). Researchers further examine the relation between institutional trading and future returns and find that institutional trading can predict future returns (Yan and Zhang, 2009). Finally, others study the institutional trading and prior institutional trading to reveal that institutions tend to trade in the same direction and engage in herding (Wermers, 1999).

There is a strong documentation that quarterly changes in institutional ownership are positively correlated with the same quarter returns (Grinblatt et al., 1995; Wermers, 1999, 2000; Bennett et al., 2003; Cai and Zheng, 2004; Nofsinger and Sias, 1999 document a similar result at an annual frequency). However, the cause of this relation remains unclear due to lack of intra period data. According to Sias et al. 2006, this positive relation is consistent with the three hypotheses: (1) aggregate institutional trading have a contemporaneous price pressure on returns; (2) institutions have information that allow them to forecast future price movements (i.e. change in institutional ownership are positively correlated with subsequent intraquarter returns); and (3) short-term institutional momentum trading. Each explanation has a different

interpretation of how prices influence institutional trading, and how institutional trading influences prices.

2.1.1 Price pressure hypothesis (the contemporaneous relation between institutional trading and stock returns)

Price pressure hypothesis suggests that institutional trading has a direct impact on stock returns. Chakravarty (2001) and Sias, Starks, and Titman (2001) suggest that the relation between changes in institutional ownership and returns measured over the same period is due to price effects associated with institutional trading. Keim and Madhavan (1997) evaluate the trades of 21 institutions over a 26 month period and find that, on average, institutional investors buy stocks at a 0.31% premium and sell stocks at 0.34% discount relative to their previous day's close. Similarly, Chan and Lakonishok (1995) evaluate the trades of 37 investment managers over an 18 month period and find evidence that institutional investors' trades have both temporary and permanent effects. The former is the price pressure effect and the latter is the informed trading effect. Sias et al. (2001) use a covariance decomposition method to estimate the relation between changes in quarterly ownership and daily returns, and conclude that institutional price pressure is the predominant explanation. There are three potential explanations for price changes associated with aggregate institutional trading: short-term liquidity effects, imperfect substitution, and information revealed through institutional trading (Sias et al., 2006).

Short-term liquidity effect suggests that buying or selling a large block of shares will move stock prices regardless of how large or efficient a particular Stock Exchange market it might be, because the demand curve for shares is downward sloping. Scholes (1972) explains that as the size of the trade increases and in order to convince investors to buy the additional shares, it might be necessary to offer a lower price than the prevailing price in the market. Holthausen, Leftwich, and Mayers (1987) relate the price impact to both the price concession given by the seller of a large block that includes compensation for the search and the inventory costs that include a risk premium. Similarly, institutions need to pay a premium when buying a large block of shares because it is difficult to find immediately willing sellers or institutions push liquidity providers away from their preferred inventory positions (Stoll, 1978; Grossman and Miller, 1988). Short-term liquidity hypothesis predicts a temporary price effect and a

quick return of prices to their equilibrium level (Kraus and Stoll, 1972).

The imperfect substitution hypothesis indicates that prices also change if there are no perfect substitutes for a particular stock. A seller has to offer a discount to induce buyers to buy additional shares, i.e. the seller faces a downward-sloping demand curve. Similarly, a buyer has to offer a premium in a larger transaction, i.e. the buyer faces an upward-sloping supply curve (Scholes, 1972). If institutional investors purchase a stock, and supply curves are upward sloping, the aggregate institutional demand will have a price impact.

Finally, if trading by institutional investors reveals information, then institutional trading will affect prices (Easley and O'Hara, 1987). Recent evidence suggests that institutional investors are better informed than other investors (Chakravarty, 2001). A number of empirical tests suggest that information revealed through trading is primarily responsible for stock price changes (Scholes, 1972; French and Roll, 1986; Barclay, Litzenberger, and Warner, 1990).

2.1.2 Informed trading hypothesis (the relationship between institutional trading and subsequent returns)

The informed trading hypothesis implies that institutions have an informational advantage that allows them to forecast returns. Chakravarty (2001) documents that institutional buying and selling decisions are influenced by private information, that changes in their holdings convey information, and therefore, large changes in holdings are more likely to be driven by private information. Thus, stocks that institutions buy outperform those they sell, and institutional trading leads to intraquarter returns.

Recent studies provide evidence that institutions are better informed than other investors and at least have some ability to forecast future abnormal returns. Chen, Jegadeesh, and Wermers (2000) find that stocks fund managers buy outperform those they sell by 2% per year after controlling for various risk characteristics. Daniel et al. (1997) and Wermers (2000) find that institutional investors outperform benchmark stocks with similar risk characteristics. Yan and Zhang (2009) observe that only short-term institutional trading can predict future returns and attribute this ability to informational

advantage. Nofsinger and Sias (1999) find that changes in institutional ownership can forecast next year's returns and also attribute this forecasting ability to informational advantage. Cohen, Gompers, and Vuolteenaho (2002) document that institutions as a group outperform individuals by 1.44 percent per annum. Coval and Moskowitz (2001) document that mutual fund managers earn abnormal returns in excess of one percent point per year on nearby investments. Pinnuck (2003) infers trades from changes in monthly portfolio holdings of Australian active equity managers and find that the stocks they buy earn abnormal returns whereas stocks they sell do not earn abnormal returns. Sias and Starks (1997) find that institutional trading reflects information and increase the speed of price adjustment. Gompers and Metric (2001) document a positive relation between institutional ownership and future stock returns; however, they attribute this relation to temporal demand shocks rather than institutions' informational advantage. In addition, Alangar, Bathala, and Rao (1999), Bartov, Rad Hakrishnan, and Krinsky (2000), and Dennis and Weston (2000) provide additional evidence that institutional investors are better informed than other investors.

On the contrary, Cai and Zheng (2004) point out that institutional trading has negative predictive power for the next quarter's returns, and attribute their results to the price pressure caused by institutional demand. Campbell, Ramadorai, and Schwartz (2009) use a complicated algorithm to measure institutional trading from 13F filling and TAQ data and find that institutional flows are negatively correlated with future short-term returns on a daily basis. This negative relation is driven by institutional sells, that is, poor performance of institutions. The mixed results may be due to the low frequency institutional holding data they employ to infer institutional trading. Chen et al. (2000) argue that the trade of a stock is more likely to represent a signal of private information than the fraction of the holding position of the stock. Bennett et al. (2003) add that institutions' ability to forecast returns is sensitive to how institutional trading is measured. Moreover, Goetzmann, Ingersoll, and Ivkovic (2000) note that daily frequency data can provide more precise estimates and sharper inferences as to measure fund managers' timing skills to fund returns.

2.1.3 Momentum trading hypothesis (the relation between institutional trading and past returns)

Momentum trading is one of the technical trading strategies which use past price movements to forecast future returns, with a belief that trends are likely to continue. If institutions follow a simple short-term momentum trading strategy, quarterly changes in institutional ownership will be positively correlated with the same quarter return. This explanation is consistent with theoretical models which suggest that smart investors may engage in a momentum trading strategy which they purchase stocks that have recently performed well and sell stocks that have performed poorly (DeLong et al., 1990; Hong and Stein, 1999). However, extant literature offers mixed results. Some researchers find strong evidence of institutional momentum trading (Bennett et al., 2003; Chen, Hong, and Stein, 2001), while others find relatively weak evidence of institutional momentum trading, for example, limited to buying of past winners (Cai and Zheng, 2004), limited to sale of small capitalization past losers (Lakonishok et al., 1992), limited to purchase of large capitalization past winners (Grinblatt et al., 1995), limited to half of the capitalization deciles (Nofsinger and Sias, 1999), limited to two smallest capitalization quintiles (Wermers, 1999). Yet other researchers conclude that institutions are not momentum traders (Gibson and Safieddine, 2003; Badrinath and Wahal, 2002; Gompers and Metrick, 2001; Falkenstein, 1996).

The precise nature of the intraquarter relation cannot be known without the high frequency institutional trading data. Some markets, such as the Finnish (Grinblatt and keloharju, 2000), Korean (Choe, Kho, and Stulz, 1999), Taiwanese (Chen and Hong, 2006) and Chinese market do record daily institutional holding information. Grinblatt and Keloharju (2000) use portfolio holding for Finnish investors to document that foreign institutions are contrarian traders and they perform well. Choe et al. (1999) find daily herding and trend chasing by Korean and foreign institutional investors but contrarian trading by individual investors. Chen and Hong (2006) use daily institutional holding information from the Taiwan Stock Exchange and find that institutions are informed traders in buying but not in selling. In other countries such as the U.S., institutional holding information is reported only quarterly, which makes it difficult to identify the times at which institutional trades occur during the quarter. This makes it hard to tell whether institutional trading within the quarter leads, lags, or is

contemporaneous with returns. Sias et al. (2006) develop a new methodology to combine monthly return data and quarterly ownership data to make at least some inferences about monthly lead and lag relations between flows and returns, however, the daily lead and lag relations still cannot be determined. Recently, several researchers employ proprietary datasets to measure high frequency institutional trading.

2.1.4 The use of proprietary datasets

A number of recent papers use proprietary datasets to study the relationship between institutional trading and stock returns because proprietary datasets offer tantalizing glimpses of the high frequency institutional trading behaviour. For example, Froot, O'Connell and Seasholes (2001) and Froot and Ramadorai (2008), employ custodial data from the State Street corporation, and find evidence of flow persistence and bidirectional positive Granger causality between weekly institutional flows and returns on equity portfolios in a variety of countries. Lee and Radhakrishna (2000) study the TORQ dataset, a sample of trades with complete identification of market participants. Jones and Lipson (2003) employ Audit Trail data from the NYSE, while Jones and Lipson (2001) and Barber and Odean (2008) use weekly data from Plexus, a transactions cost measuring service for a subset of money managers.

Griffin, Harris, and Topaloglu (2003) use the type of brokerage house to identify individual and institutional trading in Nasdaq 100 stocks from May 2000 to February 2001. They find that changes in institutional ownership is strongly contemporaneous correlated with stock returns at a daily and an intra-daily frequency. They attribute this relation to institutional intraday positive feedback trading. Moreover, they find that institutional trades cannot predict future daily returns. Still, their finding is based on a dataset that relies on broker identification, and therefore, cannot determine whether certain trades or orders are made by institutional or individual investors.

Gallagher and Looi (2006) use daily transaction data from 34 Australian equity funds managers and find that institutional trading exhibits statistically and economically significant predictive power in forecasting future stock returns on a risk-adjusted basis. Nevertheless, their sample size is too small as they only have 34 institutions trading data which does not reflect market wide aggregate institutional trading.

Ng and Wu (2007) employ a proprietary dataset similar to the NYSE's Consolidated Equity Audit Trail data from April 2001 to August 2002 and find that Chinese institutions are momentum traders, and that their trades cannot predict future stock returns. In contrast, Lee et al. (2009) claim that Chinese institutional trading has only long term predictive power for market returns, and that Chinese institution tend to be contrarian traders. The dataset of Lee et al. (2009) contains only 180 stocks out of 860, while Ng and Wu's (2007) sample stocks only accounts for 32% of the total stock turnover.

Other than the use of proprietary datasets, there have been some attempts to employ publicly available databases to measure high frequency institutional trading. For example Bozcuk and Lasfer (2005) have used block trades as a measure of institutional participation in a stock, i.e. they assume that large trades above a fixed cut-off size are institutional. However, block trades account for only a modest fraction of trading volume, which makes this method of inferring hardly accurate because institutional investors may engage in stealth trading that place small trades to hide their activities (Chakravarty, 2001).

In sum, it is only high frequency institutional holding data, i.e. daily change in aggregate institutional holding data that can accurately measure the aggregate institutional daily trading activity and offer strong evidence of price pressure, informed trading, and momentum trading of institutional investors and distinguish between them.

2.2 The relation between individual trading and stocks returns

Institutional and individual investors generally exhibit quite different trading behaviour. More precisely, institutions are not only often viewed as informed investors, but also assumed to have a long-term investment perspective, and make investment decision based on the fundamentals. In contrast, individual investors normally have a more short-term investment perspective and are often assumed to act more like noise traders (Black, 1986). Trading information about individual investors has been difficult to obtain because daily individual ownership data not available in most financial markets except for the SSE. As a result, most relations between individual trading and stock returns are observed by relying on proprietary or publicly available datasets to infer high frequency

individual trading. These restricted datasets may have several limitations as discussed in the above section.

The evidence on the performance of individuals is also mixed. Some papers find that individual trading is negatively correlated with subsequent returns, i.e. poor performance of individual investors. Dennis and Weston (2000) document that individual investors are less informed compared with institutions and insiders, which suggest that individual trading has negative return predictability. Odean (1999) employs 10,000 customer accounts from a large U.S. brokerage firm from 1987 to 1993 to reveal that stocks individual investors buy consistently under-perform those they sell. Hvidkjaer (2008) studies small trade volume to infer retail trading, and finds that stocks with intense sell-initiated volume outperform those with intense buy-initiated small trade volume. Barber and Odean (2000) use data from a discount brokerage and show that individual investors appear to over-trade and underperform. Barber, Lee, Liu, and Odean (2008) use the entire actual trade history from the Taiwan Stock Exchange and document that the aggregate portfolio of individuals suffers an annual performance penalty of 3.8%. Lee et al. (2009) claim that Chinese individual trading has predictive power for daily market returns.

In contrast, other papers find that individual trading is positively correlated with subsequent returns. Kaniel, Saar, and Titman (2008) employ the NYSE audit trail data during the 2000 to 2003 sample period. They document positive abnormal returns after intense buying by individuals and negative abnormal returns after individual sells, which suggests that individual trading predicts future short-term returns positively. They attribute this relation to risk-averse individuals who provide liquidity by contrarian trading to institutional investors. However, the dataset they use does not allow them to observe individual trading that is internalized by brokerages or routed to wholesalers. The fraction of the unobserved data is therefore likely to be large. Jackson (2003) also shows that net trades of brokerage clients positively forecast the short-term market and cross sectional returns in Australia. Coval, Hirshleifer, and Shumway (2005) find that individual who performed well in the past earn superior returns.

Yet other papers find that individual trading has no return predictability. For instance, Griffin et al. (2003) find that individual trading cannot predict future returns in the US. Barber, Odean, and Zhu (2009) find that stocks bought by clients of two U.S.

brokerage firms neither outperform nor underperform the stocks they sold. Ng and Wu (2007) find Chinese individual trading cannot predict future stock returns either.

Recent studies document that individual investors are contrarian traders in the U.S (Griffin et al., 2003; Kaniel et al., 2008); in Korea (Choe et al., 1999); in China (Ng and Wu, 2007); in Finland (Grinblatt and Keloharju, 2001) and in Australia (Jackson, 2003).

In sum, the previous literature relies on restricted proprietary data sets to infer high frequency individual trading. Using daily individual holding data will allow me to examine the relation between individual trading and past, contemporaneous, and future stock returns and their interaction with institutions.

Chapter 3

Data

This Chapter offers an overview of the Chinese stock markets, the Shanghai Stock Exchange, and institutional investors in China. And then, it provides a detailed description about the unique dataset obtained from the SSE, the Topview dataset.

3.1 The Chinese stock markets overview

The Chinese stock market has two exchanges, the SSE and the Shenzhen Stock Exchange (SZSE), which were established in November 1990 and April 1991, respectively. The SSE and the SZSE are open from Monday to Friday, and each exchange has two trading sessions: the morning session, from 9:30 until 11:30, and the afternoon, from 13:00 until 15:00. At present, there are about 1,599 companies listed on the SSE and the SZSE. China has no capital gains tax and short selling is prohibited. Both the SSE and the SZSE have limit bounds of ±10% imposed on the fluctuations of stock prices from their previous day's closing prices in order to avoid sharp price increase or decrease.

Chinese public companies have four types of shares; state-owned shares, director's shares, A-shares, and B shares. The most significant holding at 38% of market capitalisation is direct ownership by the state, which is a non-tradeable category. The market capitalization of A-shares is about 10-20 times larger than that of B-shares. A-shares are also much more actively traded every day. Since February 2001, the Chinese government has opened the B-Share market for Chinese domestic investors. The popularity of the market to retail investors is primarily driven by a lack of alternative investment opportunities. There is a widely held view that the lack of sophistication of investors causes them to rely on rumours for information. The excessive price movement and speculative activities are common in the Chinese stock market and Chinese investors prefer short-term to a long-term investment objective (Mei et al., 2004).

3.1.1 Institutional investors in China

Institutional investors in China consist of (i) investment funds, (ii) Qualified Foreign Institutional Investors (QFIIs), (iii) the National Social Security Fund, (iv) insurance companies, (v) corporate annuity funds, and (vi) authorized securities firms. Each investor is allowed to open one trading account on each of the two stock exchanges. Before they trade securities, investors need to register their accounts at the China Securities Depository and Clearing Corporation Limited, which is a national securities registration institute under the supervision of the China Securities Regulatory Commission. Institutional investors are not allowed to open individual trading accounts, and vice versa. An institution can only place orders through one branch of a brokerage firm.

3.1.2 The Shanghai Stock Exchange

The SSE is one of the most actively traded stock exchanges in the world, and the biggest stock exchange in China with 861 stocks traded. The SSE is governed by the China Security Regulatory Commission and is still not entirely open to foreign investors due to tight capital account controls exercised by the Chinese mainland authorities. Furthermore, the SSE is an order-driven market without a designated market maker. It runs an electronic automated trading system, while only limit orders can be stored in the limit order book in the SSE. Currently, the best five bid and ask prices and the corresponding depths of the book are revealed continuously to the public investors. The tick size (minimum price variation unit) is 0.01 RMB while the minimum trading quantities unit is 100 shares.

Like many other emerging markets, the SSE has relatively immature infrastructure such as an inadequate disclosure, an opaque legal and governance framework, and an inexperienced regulator (Lu and Lee, 2004).

In 2007, the total turnover on the SSE was US$ 5,588 billion, which was 313.47% more than in the previous year. Stock transactions were US$ 4,492 billion, representing 80.37% of the SSE's total turnover. The daily average stock transactions were US$ 18.56 billion, 426% higher than those in 2006. It is also worth mentioning that daily fund transactions hit US$ 261.2 million, 317.88% more than in the previous year. When calculated by tradable shares, the turnover rate of stocks was 927.193%. The total market

capitalization of the SSE hit US$3.95 trillion, making it the largest market in China and second largest market in the world.

As can be seen from Figure 3.1, the SSE was volatile during the period from 1st June 2007 to 31st December 2008. The SSE index rose from 3,821.92 to 6,124 from June 2007 to October 2007, but dropped from 6,124 down to 1664 (it dropped by 73%) from November 2007 to December 2008.

Figure 3.1 The SSE market index during sample period
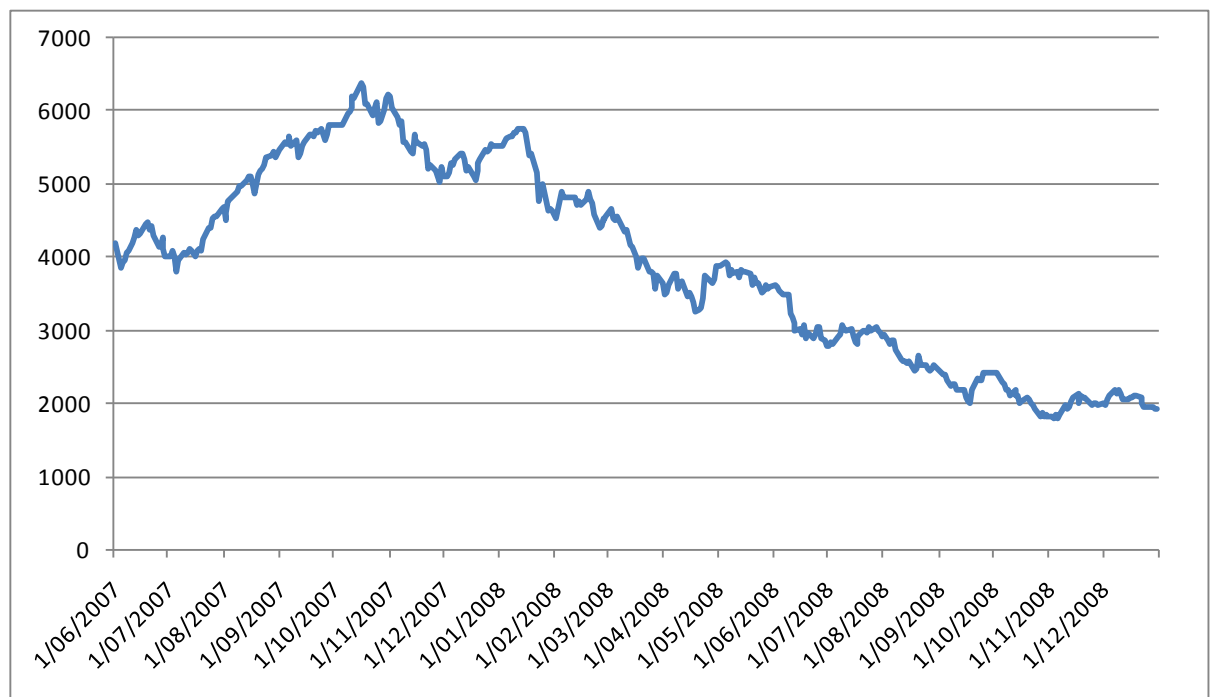
Note: The sample period from June 2007 to December 2008 covers both bull and bear period. The bull period was from June 2007 to October 2007, while the bear period was from November 2007 to December 2008.

3.2 The Topview dataset

In this research, I employ the Topview dataset which was developed by the SSE in June 2007. Topview is a series of trading data and statistics for all stocks listed on the SSE. It reveals valuable statistics, such as trading volume and prices of various types of trading accounts, which give investors a unique insight as to the identity and analysis of major market participants' trading activities in a specific stock, and help them make more effective investment decisions. However, the Topview dataset was discontinued in January 2009. The distinguishing features of the Topview dataset are described below.

The Topview dataset contains actual trading history of all market participants, obtained directly from the SSE. Thus apart from input errors, it is completely reliable. At the end of each trading day, the Topview database collects detailed daily statistics for each stock. The Topview dataset contains data on institutional (mutual funds, insurance companies, foreign institutions, and brokerage dealers), directors, and individual investors' ownership level on a daily, weekly and monthly basis. Table 3.1 provides a sample stock that we can be seen in the Topview dataset.

For each stock from the SSE and each day, we can see (1) the institutions, director and individual holdings level and number of accounts, (2) the buy, sell, net buy, and net sell amount of the top 10 accounts (this allows us to identify the type of investors that intensely buy or sell a particular stock), (3) each trader account's daily buying and selling amount, i.e. each trader's daily flow.

For each day and each stock, all accounts are categorised into 9 different accounts based on the each account's shareholding volume. The classifying criteria are: 1,000 shares, 10,000 shares, 50,000 shares, 100,000 shares, 500,000 shares, 1 million shares, 5 million shares and 10 million shares. Topview also reports an alternative classification, i.e. accounts of each investor are also categorized into 4 different accounts: small individual accounts (less than 10,000 shares), middle individual accounts (hold 10,000 to 50,000 shares), big accounts (hold between 50,000 to 1 million shares) and super big accounts (that hold more than 1 million shares).

In short, we can clearly see the shareholding of individual, directors, and institutions from the Topview data, and can closely monitor the move of each investor type at a daily frequency.

Table 3.1 Sample stock's ownership structure from the Topview dataset

Daily ownership structure – Bank of Pufa			
Date	**Individual**	**Directors**	**Institutions**
09/10/2007	3.9	44.4	51.7
10/10/2007	3.9	44.2	51.9
11/10/2007	3.8	43.9	52.3
12/10/2007	3.8	43.7	52.5
15/10/2007	3.9	43.6	52.5
16/10/2007	3.8	43.5	52.7
17/10/2007	3.9	43.1	53.0

Note: the above table shows daily ownership structure level of the Bank of Pufa from 9th Oct 2007 to 17th Oct 2007. All figures are in percentage. The institutional ownership has increased 2.45% which implies that institutions continuous buying the share of Bank of Pufa. Whereas individual ownership remains relatively constant which suggests individual investors did not trade this stock much during these days.

Chapter 4

Methodology

This chapter discusses the event study methodology and procedures that will be employed to carry out the empirical testing.

The event study methodology is widely used in the field of finance to test the impact of a certain event on the price of an asset. We can use the event study methodology to test a certain event on a stock's pre-event, event period and post-event day stock returns. For example, Kaniel et al. (2008) use the event study methodology to test individual investors trading on stock prices. Specifically, they rank all stocks and form 10 equal-weighted deciles based on the Net Individual Trading (NIT) measure each week. The decile 1 contains stocks with the most intense selling (the negative NIT), while the decile 10 contains stocks with the most intense buying (the positive NIT). After creating time series portfolios with intense individual trading imbalance, Kaniel et al. (2008) calculated the market adjusted abnormal returns and cumulative abnormal returns one month before and after the intense individual trading week. They find that the NIT is positively related to future short horizon returns. I will apply Kaniel et al.'s (2008) approach to carry out the empirical testing.

The sample period is from 1st June 2007 to 31st December 2008, where there were 392 trading days. Since each trading day can be treated as an event day, therefore, I have 392 event days. My aim is to compute the market adjusted average abnormal returns and cumulative market-adjusted average abnormal returns around intense buying and selling activity of institutional and individual investors.

I first need to create the precise measure of daily net institutional and individual trading. The Topview dataset contains daily institutional and individual ownership for each stock on a daily basis. I define the daily change in institutional and individual ownership as a difference between the event day t ownership and the lagged one day $t - 1$ ownership.

$$Own\_Change_{it} = \%Ownership_{it} - \%Ownership_{i(t-1)} \,, \qquad\qquad 4.1$$

where *%Ownership$_{it}$* is the percentage of the stock *i* held by institutions (individuals) at time *t*. *%Ownership$_{i(t-1)}$* is the percentage of stock *i* held by institutions or individuals at time *t −1*.

The institutional and individual ownership change is the same as the difference between the institutional and individual daily buy amount and sell amount (daily net flow) scaled by the lagged one day market capitalization. I can use the daily change in ownership to measure the net daily institutional and individual trading activity precisely, the larger the change in stock ownership, the higher the intensity of their trading. For example, the most positive change in stock ownership reveal the most intense net buying.

Having created the measure of institutional and individual trading, I rank all stocks (860 stocks) by their daily change in institutional ownership from 1st June 2007 to 31st December 2008 and assign them to one of the 10 decile. So I have ten equal-weighted deciles (each decile contains 86 stocks). The decile 1 contains the stocks with the most intense institutional buying (most positive change in institutional ownership), the decile 10 contains stocks with most intense selling (most negative change in institutional ownership), and the other deciles contain stocks with relative low level or no institutional trading. For added detail, I subdivide the top and bottom deciles into four sub deciles: decile 1A, 1B, 1C, and 1D, and decile 10A, 10B, 10C, and 10D where each sub-decile contains 21 stocks. By repeating this procedure every day in the sample period, I get a time-series of the 10 equal-weighted deciles and 8 equal-weighted sub-deciles. The procedure is the same for individual trading. For each decile, I follow Kaniel et al. (2008) to compute the daily market adjusted abnormal returns 20 days prior to and 20 days after the ranking day. The return computations exclude non-trading days such as public holidays. I then investigate the relationship between the daily change in institutional (individual) ownership and past, contemporaneous, and future stock returns.

The procedures to calculate abnormal returns and cumulative abnormal returns are as follows. The event here is the intensity of institutional and individual trading. To determine whether this event has a significant impact on stock prices, I first need to

think about how the price would behave in the absence of the event, that is, the normal behaviour $E[R_{it}|X_t]$.

There are three models that are commonly used to describe the normal behaviour of the price of an asset. One is the Constant Mean Return Model, where X_t is a constant assuming that the mean return of a given security is constant through time. The second is the market model where X_t is the market return assuming a stable linear relation between the market return and the security return. The market model is frequently used in literature. It is based on the Capital Asset Pricing Model (CAPM) and assumes that the normal behaviour of an asset can be described by its degree of co-movement with a market index. For any security i, we have:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it},$$
4.2

where R_{it} and R_{mt} are period t returns on the security i and the market portfolios, respectively, α_i, β_i are the parameters of the market model, and ε_{it} is the zero mean disturbance term.

Finally, the market adjusted model is an often used version of the market model, where $\alpha = 0$, $\beta = 1$, that is, the abnormal return is equal to the individual stock raw return subtracts market return.

Once we get a benchmark for the normal behaviour of the stock, we can define the abnormal behaviour:

$$AR_{it} = R_{it} - E[R_{it}|X_i],$$
4.3

where AR_{it} is the abnormal return, R_{it} is the observed or actual return and $E[R_{it}|X_t]$ is the normal or expected return of the stock i on day t.

According to Campbell, Lo, and MacKinlay (1997), the choice of the model is less important. The selection of a particular model has only a small impact on the outcome

of the event study, which implies that my results are not likely to be a consequence of model selection. I follow Kaniel et al. (2008) to use the market adjusted model.

For each trading day, I compute each decile's daily market adjusted abnormal return AR_{it} from the days -20 to 20.

$$AR_{it} = R_{it} - R_{mt},$$
<div align="right">4.4</div>

where R_{it} is the raw return of the decile i on day t (I use daily adjusted closing prices[7] from Datastream). R_{mt} is the return on the Shanghai Stock market index (the equal-weighted portfolio of all stocks in the sample) on day t. (I use the daily adjusted closing SSE's A share market index from Datastream[8]).

The time series of daily abnormal returns can then be averaged to obtain the mean abnormal returns:

$$AAR_{it} = \frac{1}{N} \sum_{1}^{N} AR_{it},$$
<div align="right">4.5</div>

where AAR_{it} is the mean average abnormal return of the decile i on the day t, and N is the number of trading days.

The significance of AAR_{it} at each observation can be tested by computing the test statistic

$$t_{it} = \frac{AAR_{it}}{S.E.(AAR_{it})},$$
<div align="right">4.6</div>

Where the *t-statistic* is estimated by using Newey-West's (1987) heteroskedasticity consistence coefficient covariance matrix to calculate the standard error due to potential autocorrelation of the errors induced by overlapping periods.

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[7] The adjusted closing stock prices account for stock splits, dividends and rights offerings etc.
[8] The adjusted closing market index account for stock splits, dividends and rights offerings etc.

I obtain the significance level by checking the *t-statistic* in the student's *t*-distribution table[9]. Specifically, AAR_{it} is significant at the 10% level when the *t-statistic* is between 1.65 to 1.96, at the 5% level when the *t-statistic* is between 1.96 to 2.58, at the 1% level when the *t-statistic* is equal to or above 2.58.

The time series of the daily abnormal returns can then be summed to compute cumulative abnormal returns, which are then averaged to obtain the mean cumulative abnormal returns.

The cumulative average market adjusted returns (CAR_{it}) and the mean cumulative average abnormal returns ($CAAR_{it}$) are calculated as follow:

$$CAR_{it} = \sum_{T_1}^{T_2} AR_{it} \qquad\qquad 4.7$$

The mean cumulative average abnormal return ($CAAR_{it}$) is calculated as follows:

$$CAAR_{it} = \sum_{t=t_1}^{t_2} AAR_{it} \qquad\qquad 4.8$$

I can test for the significance of $CAAR_{it}$ at each observation by computing the test statistic:

$$t_{it} = \frac{CAAR_{it}}{S.E.\ (CAAR_{it})} \qquad\qquad 4.9$$

$CAAR_{it}$ is also a time series mean. Therefore, the *t-statistic* is computed using Newey-West's (1987) correction, i.e. *S.E. ($CAAR_{it}$)* is Newey-West's (1987) standard error.

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[9] the student's t-distribution table is from Wooldridge (2003) P817.

Chapter 5

Results

This chapter presents the results. The first part discusses the results of the relation between the daily institutional trading and contemporaneous, future, and past stock returns. The second section discusses the results of the daily individual trading and stock returns.

5.1 Daily Institutional Trading and Stock Returns

5.1.1 Contemporaneous relation (price pressure of institutional trading)

The price pressure hypothesis suggests that if aggregate institutions increase (decrease) their holdings of a certain stock, then their buying (selling) activity would push up (down) the price of the stock, that is, institutional trading has an impact on stock prices. I can test whether there is price impact of institutional trading by examining the abnormal returns (AR_{it}) on the ranking day. If the abnormal returns are significantly positive for the intense institutional buying portfolios, but significantly negative for the intense selling portfolios on the ranking day, then the intense institutional trading have an impact on stock prices. If abnormal returns are zero for all the intense institutional deciles, then this suggests that institutional trading do not have an impact on stock prices.

My unique dataset allows me to accurately measure the impact of aggregate institutional trading on stock prices at a daily frequency. From Table 5.1 Column 2, and Figure 5.1.1, the abnormal returns exhibit interesting patterns for the intense institutional buying and selling portfolios on the ranking day. It appears that the higher the intensity of institutional trading, the greater the magnitude of abnormal returns. Specifically, the intense institutional buying portfolios (decile 1, 1A, 1B, 1C, and 1D) experience significant positive abnormal returns, which are 1.16%, 2.12%, 1.19%, 0.83%, and 0.57%, respectively, whereas the intense selling portfolios (decile 10, 10A, 10B, 10C, and 10D) experience significant negative abnormal returns, which are -0.73%, -.0.53%, -0.63%, -0.78%, and -1% respectively. All abnormal returns of the intense institutional trading portfolios are statistically significant at the 1% level. The abnormal returns of all

other deciles with less or no institutional trading are statistically insignificant except for the decile 9 (AR=-0.27, t=-3.34). The result suggests that the intense buying activity pushes prices up whereas the intense selling activity pushes prices down on the ranking day, which is consistent with the price pressure hypothesis. It is consistent with Kraus and Stoll (1972), Chan and Lakonishok (1995), Keim and Madhavan (1997), and Campbell et al. (2009) that institutional trades push prices.

The difference between the decile 1 and the decile 10 is 1.89% and is statistically significant. The difference between the decile 1A and the decile 10D is 3.11%, and is also statistically significant. Assuming there were 250 trading days per year, the difference would be 778% per annum (3.11% x 250 = 778%). The result suggests that daily changes in institutional ownership are positively correlated with contemporaneous returns. This is consistent with Wermers (1999) and Nofsinger and Sias's (1999) finding that reveals a strong positive contemporaneous relation between institutional trading activity and quarterly and annual returns in the U.S. This result is also consistent with Griffin et al.'s (2003) results at a daily level, where the difference between their high and low imbalance deciles is 7.98% per day, which is considerably larger than the difference I find in this study. Nofsinger and Sias (1999) compute a similar measure using a small sample on a daily basis with 114 NYSE firms to find a difference of 2.68%, which is similar to my finding.

The above results show the overall price impact induced by institutional trading is economically significant, which has important implications. First, the price impact cost is one of the implicit transaction costs faced by market participants, which can be minimised. The price impact generated by institutional trading reveals that institutional investors face a substantial price impact cost if they pursue short-term trading strategies. In particular, the price impact cost is likely to be largest with investment strategies that require instantaneous trading. Second, institutional trading causes high volatility of the market which is likely to destabilise the financial market, and reduce its efficiency. Third, price pressure moves prices, not fundamentals, which might drive stock prices away from their fundamental levels thereby destabilising stock prices on the market. Because of these implications, the behaviour and measurement of the price impacts associated with institutional trading are of enormous importance to regulators and policy makers concerned with promoting market liquidity and expanding the institutional base, such as an increase in the number of institutions, as well as to

Figure 5.1.1 the Daily Abnormal Returns around Institutional Trading
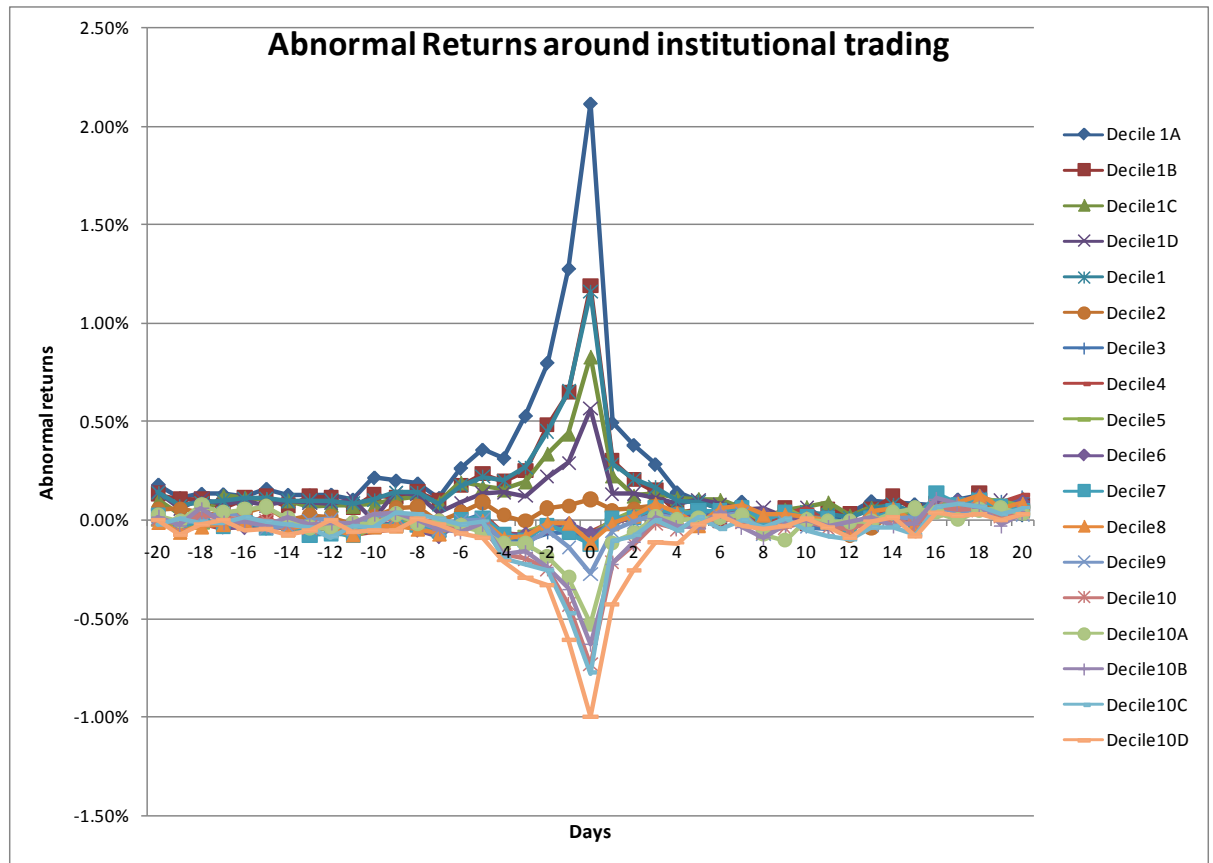
Note: the graph shows the daily market adjusted abnormal returns for portfolios sorted by daily change in institutional ownership from day -20 to day 20. The sample period is from 1st June 2007 to 31st December 2008. Each trading day, I divide all stocks based on daily change in institutional ownership and form 10 equal-weighted deciles and 8 sub-deciles. Decile 1 contains stocks that have intense institutional buying activity; decile 10 contains stocks that have intense institutional selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample.

investors who seek investment returns with minimal price impact costs.

Furthermore, I find a price impact asymmetry between institutional purchases and sales. The intense institutional buying activity has a double the impact on stock prices, compared with that of intense selling on the ranking day. This is consistent with the finding of Kraus and Stoll (1992), Chan and Lakonishok (1993, 1995), Keim and Madhavan (1997) and Kalay, Sade, and Wohl (2004), revealing that institutional buys tend to be more informative and costlier to complete than institutional sells[10]. Chan and Lakonishok (1993) provide a behavioural explanation suggesting that most managers buy stocks that are undervalued, and will buy more if the price of such stocks increases, which causes further price pressure. On the other hand, if the stock price falls, managers may defer selling in the hope that the price will revert to its fundamental value. This is the well-known disposition effect first documented by Shefrin and Statman (1985), which shows that investors tend to hold losers too long. Indeed, Garvey, and Murphy (2004) find that professional traders are also subject to the disposition bias, and that they hold their losing trades much longer than their winning trades during the day.

In sum, I find three important results. First, there is a strong positive contemporaneous relation between change in institutional ownership and stock returns at a daily level. Intense institutional trading has a significant impact on stock prices. Second, the price impact of intense institutional trading is highly economically significant, which increases institutions' total trading cost as well as the volatility of the financial market. Finally, I find that institutional purchases have a bigger price impact than institutional sales.

5.1.2 Subsequent returns after institutional trading (informed trading hypothesis)

Recent studies document that institutional investors are on average better informed than other investors and that their trading can forecast future returns (Chakravarty, 2001). If institutional trading has return predictability, I expect stocks they buy to outperform those they sell. I test this hypothesis by examining whether stock prices continue to increase (decrease) after intense institutional buying (selling), i.e. testing the significance of cumulative abnormal returns from day 1 to 20 (CAR (1, 20)). Specifically, if the CARs (1, 20) are significantly positive for the intense institutional

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[10] Saar (2001) provides a theoretical analysis of the asymmetry between buys and sells.

buying portfolios and significantly negative for the selling portfolios, then this suggests that intense institutional trading has positive predictive power for future returns. And I can make a profit by constructing a simple trading strategy that long the decile 1A stocks and short sell the decile 10D stocks. If the CARs (1, 20) are insignificant for all the deciles, then this suggests that institutional trading cannot predict future returns

Cumulative Abnormal Returns from day 1 to 20

From Table 5.1, the CARs (1, 20) are significantly positive for all the intense institutional buying portfolios (decile 1 to 1D), whereas for all the intense selling portfolios (decile 10 to 10D) are statistically insignificant. Specifically, the CARs (1, 20) for decile 1 to 1D are 1.62%, 2.19%, 1.51%, 1.56% and 1.26%, respectively, and are all statistically significant, whereas for decile 10 to 10D they are statistically insignificant. The difference between the decile 1A and the decile 10D and between the decile 1 and the decile 10 are 3.23% and 2.04%, respectively, and are all statistically significant at the 1% level. The result shows the higher the intensity of institutional buying, the greater the magnitude of positive CARs in the following 20 days but CARs are insignificant for intense selling portfolios. These patterns clearly indicate that stocks intensely bought by institutions outperform those they intensely sold, the visual evidence at which can be clearly seen from Figure 5.1.2. It also suggests that intense institutional buying has positive return predictability, whereas intense selling does not have return predictability. This result is inconsistent with the finding of Griffin et al. (2003), suggesting that the institutional buy-sell imbalance cannot predict future daily returns, and with the finding of Ng and Wu (2007), suggesting that institutional trades do not have return predictability in China.

To demonstrate the economic significance of the relation between intense institutional trading and subsequent returns, I construct a simple trading strategy: At the start of each trading day, I invest 1/20 of my fund to buy the decile 1A stocks and short sale the decile 10D stocks, and then hold them for 20 days (based one day lag change in institutional ownership). Repeating this exercise every day for 20 days allows me to make a profit of 3.23% by the end of the 20th day. By rolling the strategy forward and the annual profit would be 38.76% (3.23% x 12 = 38.76%). If I change my holding period to 5 days, I can make a profit of 81.2% per annum (2.32% x 35 weeks = 81.2%).

Table 5.1 Institutional Trading and Stock Returns

Decile	RAW(t=0)	AR (t=0)	CAR (1, 20)	CAR (1, 5)	CAR (6, 20)	CAR (-1, -20)	CAR (-1, -5)	CAR (-6 ,-20)
1A	1.91***	2.12***	2.19***	1.39***	0.80	5.55***	3.27***	2.28***
	10.03	*18.11*	*2.71*	*4.31*	*1.17*	*5.72*	*8.09*	*3.06*
1B	0.98***	1.19***	1.51**	0.75**	0.76	3.49***	1.82***	1.67**
	5.88	*12.28*	*2.02*	*2.43*	*1.2*	*3.97*	*5.19*	*2.39*
1C	0.63***	0.83***	1.56**	0.7**	0.86	2.66***	1.28***	1.36**
	3.86	*10.2*	*2.05*	*2.4*	*1.33*	*3.12*	*3.61*	*2.02*
1D	0.36**	0.57***	1.26*	0.58**	0.68	2.29***	0.92***	1.37**
	2.28	*6.86*	*1.66*	*2.01*	*1.08*	*2.86*	*2.88*	*2.09*
1	0.96***	1.16***	1.62**	0.85***	0.77	3.47***	1.8***	1.66**
	5.75	*13.04*	*2.15*	*2.89*	*1.21*	*4.06*	*5.23*	*2.46*
2	-0.1	0.11	0.5	0.22	0.28	0.72	0.25	0.47
	-0.62	*1.58*	*0.6*	*0.72*	*0.4*	*0.87*	*0.76*	*0.68*
3	-0.29*	-0.08	0.63	0.1	0.53	-0.62	-0.29	-0.33
	-1.76	*-0.87*	*0.6*	*0.25*	*0.62*	*-0.57*	*-0.72*	*-0.32*
4	-0.27	-0.06	0.78	0.13	0.65	-0.6	-0.17	-0.43
	-1.64	*-0.66*	*0.73*	*0.32*	*0.74*	*-0.54*	*-0.39*	*-0.47*
5	-0.28*	-0.08	0.82	0.19	0.64	-0.69	-0.24	-0.44
	-1.74	*-0.80*	*0.77*	*0.46*	*0.72*	*-0.62*	*-0.55*	*-0.49*
6	-0.27*	-0.07	0.68	0.09	0.59	-0.77	-0.24	-0.53
	1.73	*-0.71*	*0.65*	*0.22*	*0.68*	*-0.7*	*-0.56*	*-0.58*
7	-0.33**	-0.12	0.81	0.16	0.65	-0.71	-0.25	-0.45
	-2.05	*-1.23*	*0.76*	*0.41*	*0.73*	*-0.63*	*-0.59*	*-0.49*
8	-0.32**	-0.11	0.77	0.11	0.66	-0.7	-0.19	-0.51
	-1.94	*-1.16*	*0.75*	*0.27*	*0.78*	*-0.65*	*-0.48*	*-0.57*
9	-0.48***	-0.27***	0.1	-0.03	0.13	-0.52	-0.43	-0.09
	-2.99	*-3.34*	*0.12*	*-0.09*	*0.18*	*-0.61*	*-1.21*	*-0.14*
10	-0.94***	-0.73***	-0.42	-0.41	-0.01	-1.24	-1.09***	-0.15
	-5.03	*-7.2*	*-0.45*	*-1.18*	*-0.02*	*-1.39*	*-3.02*	*-0.21*
10A	-0.73***	-0.53***	-0.01	-0.15	0.13	-0.61	-0.77***	0.16
	-4.16	*-5.47*	*-0.02*	*-0.43*	*0.19*	*-0.75*	*-2.26*	*0.24*
10B	-0.84***	-0.63***	-0.31	-0.4	0.09	-1.01	-0.94***	-0.07
	-4.65	*-6.33*	*-0.33*	*-1.14*	*0.12*	*-1.17*	*-2.65*	*-0.1*
10C	-0.98***	-0.78***	-0.33	-0.21	-0.12	-1.3	-1.15**	-0.15
	-5.2	*-7.46*	*-0.36*	*-0.58*	*-0.16*	*-1.44*	*-3.16*	*-0.21*
10D	-1.21***	-1.00***	-1.04	-0.93**	-0.11	-2.06**	-1.52***	-0.54
	-5.6	*-7.58*	*-1.02*	*-2.36*	*-0.13*	*-1.96*	*-3.52*	*-0.66*
1-10	1.89***	1.89***	2.04***	1.27***	0.77***	4.7***	2.9***	1.8***
	25.32	*25.32*	*6.22*	*6.83*	*2.88*	*15.2*	*14.9*	*9.09*
1A-10D	3.11***	3.11***	3.23***	2.32***	0.91**	7.61***	4.8***	2.81***
	25.68	*25.68*	*7.04*	*8.76*	*2.45*	*15.01*	*15.28*	*8.45*

Notes: Table 5.1 presents abnormal returns and various periods' cumulative abnormal returns around intense institutional trading. The sample period is from 1st June 2007 to 31st December 2008. Each trading day, I divide all stocks based on daily change in institutional ownership and form equal-weighted 10 deciles and 8 sub-deciles. Decile 1 contains stocks that have intense institutional buying activity; Decile 10 contains stocks that have intense institutional selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample. Numbers in italic are Newey-West *t-statistics* *** Significant at 1% level ** Significant at 5% level * Significant at 10% level. All figures are in percentage.

Cumulative Abnormal Returns from day 1 to 5

From Figure 5.1.1, I notice sizeable abnormal returns after the ranking day, which is around day 1 to 5. It is likely that the sizable abnormal returns are a consequence of the continuing price pressure effect induced by institutional herding and/or order splitting. Herding refers to buying (selling) the same stocks as other institutions investors buy (sell). Institutional herding is well documented in the finance literature (Lakonishok, Shleifer, and Vishny, 1992; Nofsinger and Sias, 1999; Wermers, 1999; Sias, 2004). Herding may occur due to slowly diffusing private information (Hong and Stein, 1999), career concerns (Scharfstein and Stein, 1990), or due to information inferred from other traders (Bikhchandani, Hirshleifer, and Welch, 1992). Order splitting means that institutions split their orders over several days in order to hide their trades and minimise their price impact (Chan and Lakonishok, 1995). To minimise the continuing price impact induced by herding and/or order splitting immediately after the ranking day, I divide the CAR (1, 20) into two periods: the cumulative average abnormal returns from day 1 to 5 (hereafter CAR (1, 5)) and the cumulative average abnormal returns from day 6 to 20 (hereafter CAR (6, 20)).

If the CARs (1, 5) are significantly positive for the intense buying portfolios and significantly negative for the intense selling portfolios, then this suggests herding and/or order splitting which means that the sizeable abnormal returns from day 1 to 5 is a price pressure effect. From Table 5.1, the CAR (1, 5) for all the intense buying portfolios are all significantly positive whereas for the intense selling portfolios they are statistically insignificant, except for the decile 10D (CAR is -0.93%, t = -2.36). The differences between decile 1 and decile 10 and between the decile 1A and the decile 10D are 1.27% (t = 6.83), 2.32% (t = 8.76), respectively. The results here indicate the evidence of institutional herding and/or order splitting.

Cumulative Abnormal Returns from day 6 to 20

If the CARs (6, 20) are significantly positive for the intense institutional buying portfolios, but significantly negative for the intense selling portfolios, it suggests that institutional trading has return predictability which is more related to information. From Table 5.1, the CARs (6, 20) for all the deciles are statistically insignificant. However, the difference between the decile 1A and the decile 10D is 0.91%, the difference between the decile 1 and the decile 10D is 0.77% and both are statistically significant. It

Figure 5.1.2 Returns following intense institutional trading
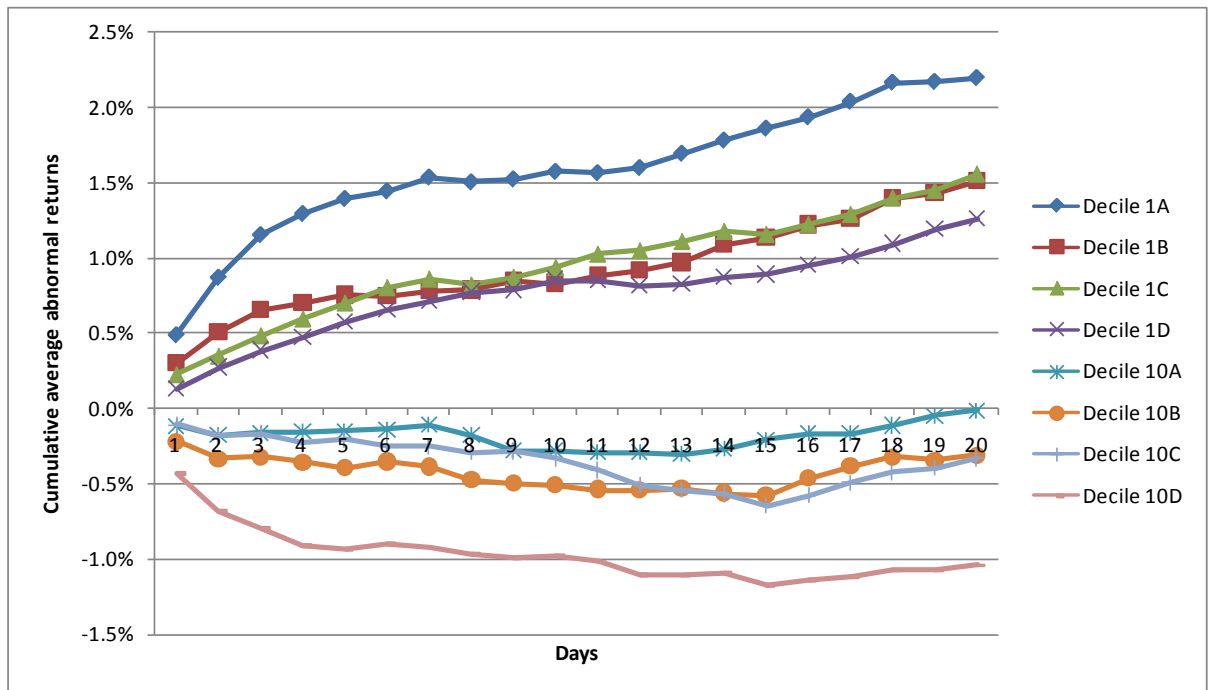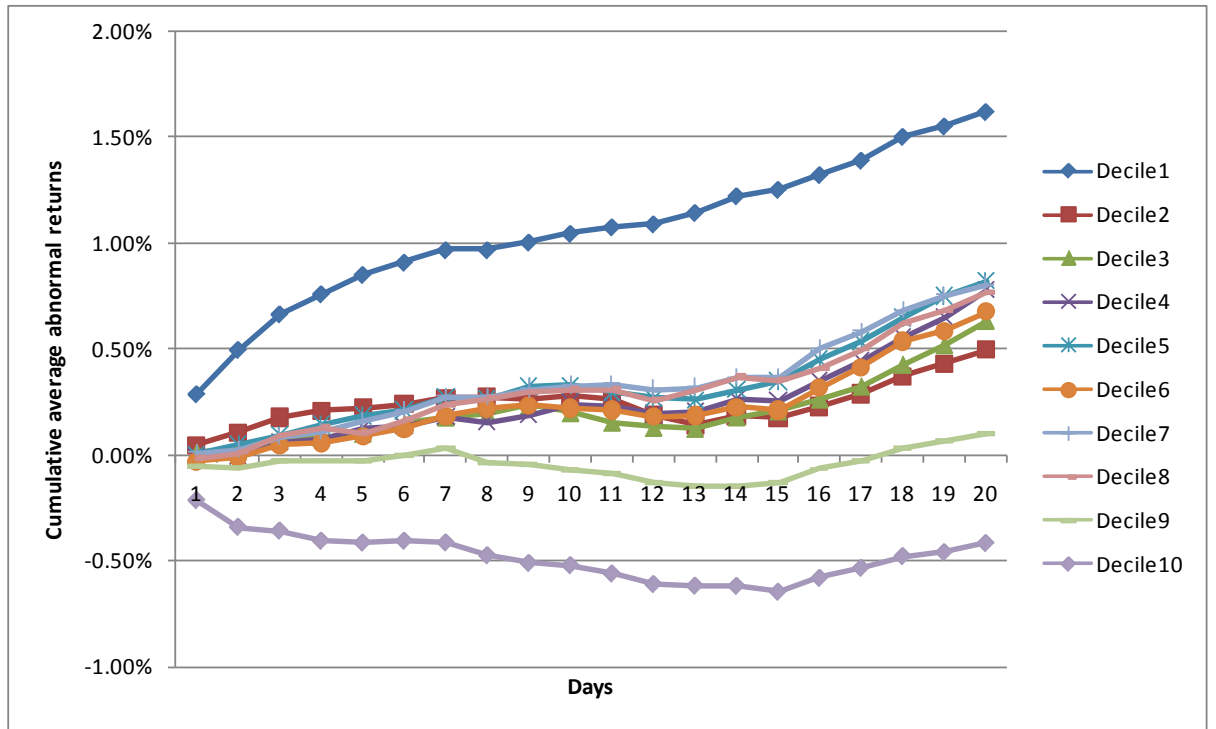
Note: Each trading day from 1st June 2007 to 31st December 2008, I divide all stocks based on daily change in institutional ownership and form equal-weighted 10 deciles and 8 sub-deciles. Decile 1 contains stocks that have intense institutional buying activity; Decile 10 contains stocks that have intense institutional selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample.

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Figure 5.1.3 Cumulative average returns from day 6 to 20 - Institutions
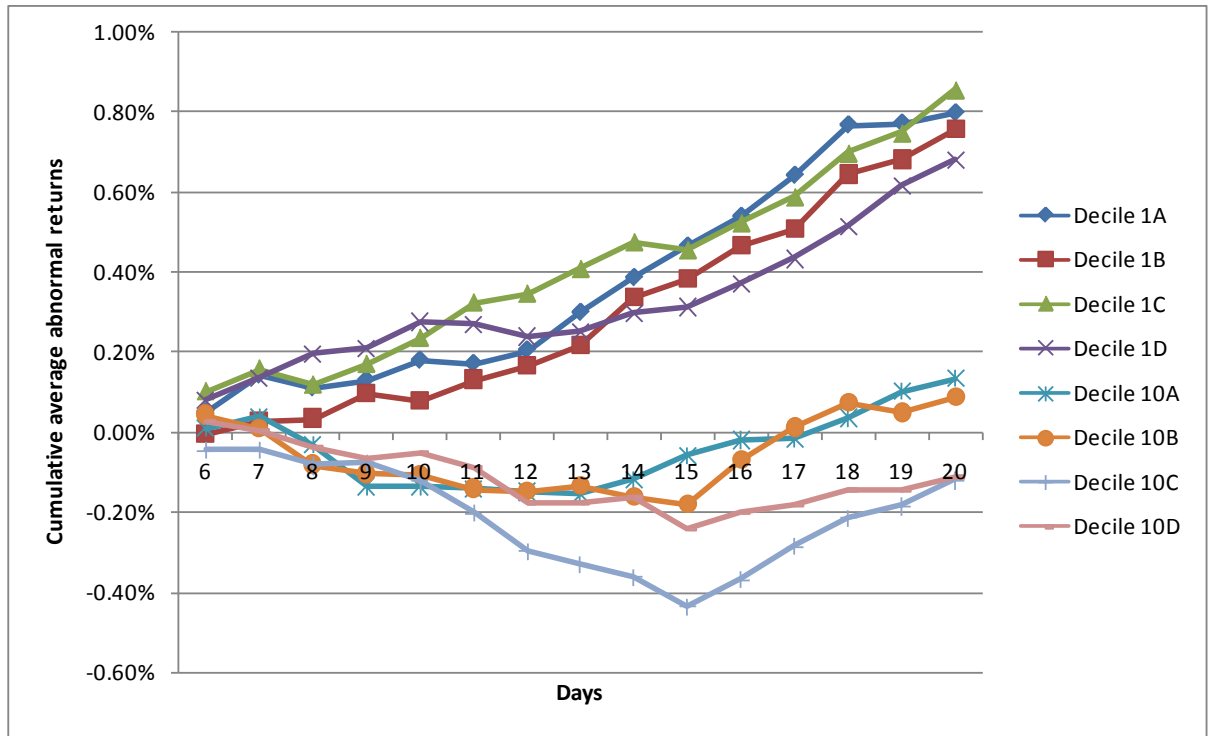
Note: Each trading day from 1st June 2007 to 31st December 2008, I divide all stocks based on daily change in institutional ownership and form equal-weighted 10 deciles and 8 sub-deciles. Decile 1 contains stocks that have intense institutional buying activity; Decile 10 contains stocks that have intense institutional selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample.

suggests that stocks intensely bought by institutions outperform those intensely sold from day 6 to 20, the visual evidence of which can be clearly seen in Figure 5.1.3.

According to Sias et al. (2001), the price pressure results on the ranking day are consistent with the information or the short-term liquidity hypothesis. If price pressure induced by institutional trading results from information, the price changes associated with the changes in institutional ownership should be permanent (return continuation). Alternatively, if the temporary liquidity constraints are responsible for price pressure, price changes should be temporary (return reversal). The results show that price changes tend to be permanent after intense institutional buying (prices remain high). This suggests that institutional investors are better informed that allow them to forecast future returns. In contrast, I find that price changes are temporary after intense selling, as they revert to their prior level, suggesting that institutional sells is consistent with the liquidity hypothesis. Overall, this so called permanent price impact asymmetry is consistent with the empirical research on block transactions and institutional trades, suggesting that markets react differently to buy and sell orders. Kraus and Stoll (1972) find that block purchases have a larger permanent price impact than block sales. The same result is documented for institutional trades (Chan and Lakonishok, 1993) and for institutional trade packages (Chan and Lakonishok, 1995).

Chan and Lakonish (1993) provide several explanations. First, concerning the information effect, a decision to buy a stock is likely to convey good firm-specific news. In contrast, institutional sales are mainly due to liquidity-motivated reasons, such as mechanical trading rules which do not necessarily convey negative information. Keim and Madhavan (1995) add that institutional buys are more likely to be based on private information than sells are because it implies a choice of one stock among all the stocks in the market but usually limit themselves to selling those stocks they already own due to restrictions on short sales (short selling is prohibited in China). Second, it could be that brokers are willing to accommodate institutional sales by purchasing shares in exchange for short-term price concessions, but are reluctant to accommodate institutional purchases which may involve taking short positions. Due to the asymmetric relationship of liquidity provision, institutional purchases are less likely to include temporary price concessions. This explanation is consistent with the finding of Campbell et al. (2009), suggesting that institutions are particularly likely to demand liquidity when they sell stocks. Saar (2001) develops a model in which the price impact

corresponds to the change in market expectations of the true value of the stocks. Further investigation into the underlying economic reasons for the return asymmetry following institutional short-term buy and sell is beyond the scope of this study.

5.1.2.1 The Capital Asset Pricing Model (CAPM) test

Although I observe that performance of the intense institutional buying portfolios outperform the intense institutional selling portfolios. It could be due to that intensely bought stocks are riskier and thus will generate higher expected returns in the future than those intensely sold stocks. I therefore employ the CAPM [11] to test if the subsequent raw returns can be explained by the market risk. The CAPM estimates the following time series regression:

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{rf}) + \varepsilon_{it}, \qquad 5.1.1$$

where, R_{it} is the 5 or 20 days holding period raw returns at period t on the decile i, R_{mt} is the market index return at period t (the SSE A share market index from datastream), R_{ft} is the daily risk free rate at period $t^{[12]}$; R_{mt}- R_{ft} is the market risk premium at time t, α_i is the intercept and β_i is the coefficient of market risk premium (R_{mt}- R_{ft}) and the beta coefficient is the sensitivity of the expected excess asset returns to the expected excess market returns.

From Table 5.1.1, for 5 holding days, all the intense institutional buying portfolios generate significant positive abnormal returns (significant positive α), whereas only the decile 10D generate significant negative abnormal returns (significant negative α). Specifically, the α of decile 1 to 1D are 0.162%, 0.268%,0.144%,0.14% and 0.106%, respectively and are statistically significant. The α of decile 10D is -0.16% (t=-2.08). The β_i of decile 1 to 1D are 0.95, 0.93, 0.96, 0.96, and 0.94, respectively, and are highly statistically significant. The β_i of decile 10 to 10D are 1.13, 1.08, 1.11, 1.16, and 1.17, respectively and are statistically significant at the 1% level, which suggests that excess returns are highly positively correlated with market return. More importantly, this shows that stocks intensely bought by institutions are less risky than those they intensely sold. The α of the difference between the decile 1 and the decile 10 and the difference between the the decile 1A and the decile 10D are 0.224% (t=7.48) and 0.428%

(t=9.41), respectively. The results are similar for 20 days holding period, only the intense institutional buying portfolios generate significant positive risk-adjusted abnormal returns. Specifically, the α of the decile 1 to 1D are 0.093%, 0.126%, 0.091%, 0.09%, and 0.07%, respectively, and are statistically significant. The high adjusted R-squares indicate that the market risk premium can explain the excess returns very well. The CAPM test adds support for the believe that stocks intensely bought by institutions outperform those they intensely sold.

In sum, I find that institutions are informed traders for buying decisions but not for selling decisions. Institutions profit from trade, while the most intensely bought stocks outperform those most intensely sold stocks by 3.23% in the 20 days after the ranking day. We can make profit by going long on stocks with the largest increase in institutional ownership and shorting stocks with the largest decrease in institutional ownership. Finally, the CAPM test adds support that only stocks institutions intensely bought generate significant positive risk-adjusted abnormal returns one month after buying.

5.1.3 Returns prior to institutional trading (momentum trading hypothesis)

Recent studies document that institutional investors are momentum traders (Bennett et al., 2003; Chen, Hong, and Stein, 2001) who buy stocks after they rise and sell after they fall. If institutional investors are momentum traders, we expect institutional trading to be positively correlated with the prior returns, that is, the CARs (-1, -20) are significantly positive for intense institutional buying portfolios, but significantly negative for the intense selling portfolios. If the CARs (-1, -20) are insignificant for all the deciles, it suggests that institutions are neither momentum nor contrarian traders.

Cumulative Abnormal Returns from day -1 to -20

From Table 5.1, the CARs (-1, -20) for all the intense buying portfolios are significantly positive, whereas for the intense selling portfolios they are statistically insignificant except for the decile10D. Specifically, the CARs (-1, -20) for the decile 1, 1A, 1B, 1C, 1D are 3.47%, 5.55%, 3.49%, 2.66% and 2.29%, respectively and are statistically significant. The difference between the decile 1 and the decile 10 is 4.7% and highly statistically significant.

Table 5.1.1 CAPM result of institutions trading

Decile	Holding periods - 5 days			Holding periods - 20 days		
	α	β	Adj R Square	α	β	Adj R Square
1A	0.268***	0.93***	0.71	0.126***	1.09***	0.77
	4.27	17.67		3.14	18.1	
1B	0.144**	0.96***	0.73	0.091***	1.09***	0.79
	2.34	18.35		2.39	20.24	
1C	0.14**	0.96***	0.75	0.09**	1.06***	0.78
	2.32	18.27		2.25	19.15	
1D	0.106*	0.94***	0.74	0.07*	1.03***	0.77
	1.85	18.97		1.76	18.54	
1	0.162***	0.95***	0.76	0.093**	1.07***	0.8
	2.78	18.9		2.41	19.38	
2	0.04	0.99***	0.76	0.033	1.04***	0.76
	0.67	17.26		0.77	17	
3	0.02	0.99***	0.67	0.039	1.04***	0.66
	0.25	14.35		0.7	13.26	
4	0.019	0.96***	0.65	0.042	1.02***	0.64
	0.23	13.64		0.75	13.14	
5	0.034	0.98***	0.66	0.046	1.03***	0.65
	0.42	13.76		0.83	13.25	
6	0.01	0.95***	0.65	0.031	0.98***	0.63
	0.12	13.66		0.56	13.19	
7	0.027	0.97***	0.66	0.039	0.99***	0.63
	0.34	14.22		0.7	13.06	
8	0.018	0.98***	0.67	0.043	1.02***	0.67
	0.23	14.01		0.79	14.03	
9	0.002	1.04***	0.77	0.018	1.07***	0.75
	0.03	17.42		0.38	17.13	
10	-0.062	1.13***	0.78	3.70E-05	1.14***	0.76
	0.37	19.39		0.077	15.94	
10A	-0.017	1.08***	0.75	0.015	1.09***	0.75
	-0.24	17.81		0.32	16.21	
10B	-0.061	1.11***	0.76	9.61E-05	1.14***	0.75
	-0.88	18.93		0.2	16.58	
10C	-0.016	1.16***	0.77	0.01	1.16***	0.76
	-0.23	19.35		0.24	15.9	
10D	-0.16**	1.17***	0.74	-0.022	1.17***	0.72
	-2.08	19.59		-0.42	14.5	
1-10	0.224***	-0.18***	0.25	0.09***	-0.07***	0.06
	7.48	-7.25		10.16	-4.99	
1A-10D	0.428***	-0.23***	0.18	0.147***	-0.083***	0.03
	9.41	-6.55		10.46	-3.63	

Note: The sample period is from 1st June 2007 to 31st December 2008. Each trading day, I divide all stocks based on daily change in institutional ownership and form 10 equal-weighted deciles and 8 sub-deciles. Decile 1 contains stocks that have intense institutional buying activity and decile 10 contains stocks that have intense institutional selling activity. *** Significant at 1% level; ** Significant at 5% level; * Significant at 10% level. All figures are in percentage. Numbers in italic are Newey-West corrected *t-statistics*.

Cumulative Abnormal Returns from day -1 to -5

From Figure 5.1.1, I also observe sizeable abnormal returns several days (day -1 to -5) prior to the ranking day. The significant abnormal returns may due to herding and/or order splitting. Thus, I divide the CAR (-1, -20) into two periods: the CAR (-1, -5), and the CAR (-6, -20). If the CARs (-1, -5) are significantly positive for the intense buying portfolios, but significantly negative for intense selling portfolios, then this suggests the existence of institutional herding and/or order splitting.

From Table 5.1, the CARs (-1, -5) are significantly positive for the intense buying portfolios, but significantly negative for the intense selling portfolios. From Figure 5.1.1, it is interesting to notice that the closer it is to the event day, the greater the magnitude of the abnormal returns is. This pattern shows the intensity of the institutional buying and selling activity is getting higher and higher closer to the ranking day. These results indicate evidence of herding and/or order splitting. To minimise the price impact induced by these two effects, I turn to examine the CARs (-6, -20).

*Cumulative Abnormal Returns from day -6 to -20*

If the CARs (-6, -20) are significantly positive for intense buying portfolios, but significantly negative for the intense selling portfolios, it suggests that institutional trading is positively correlated with the prior returns, that is, institutions are momentum traders. From Table 5.1, the CARs (-6, -20) for the intense buying portfolios are significantly positive, whereas for the intense selling portfolios are statistically insignificant. Specifically, the CARs (-6, -20) for the decile 1 to 1D are 1.66%, 2.28%, 1.67%, 1.36% and 1.37%, respectively, and are statistically significant whereas for the decile 10 to 10D they are statistically insignificant. This result shows strong evidence that institutions are momentum traders for buying but not for selling. This result is consistent with the finding of Cai and Zheng (2004), as well as that of Grinblatt et al. (1995) who find 77% of the mutual funds are momentum traders, buying past winners but not selling past losers. The result is partly consistent with recent studies find strong evidence that institutions are momentum traders for both buys and sells (Bennett et al., 2003; Chen et al., 2002).

In sum, the results indicate strong evidence that institutions are momentum traders for buying but not for selling and this may due to short selling restrictions in China.

5.1.4 The rank correlation test

I apply the Spearman's rank correlation for robustness testing. Precisely, I calculate the Spearman's rank correlation coefficients between the institutional ranking on the event day and the ranking of each day from day -20 to 20, and I repeat this procedure for each trading day to get the average Spearman's rank correlation coefficients from day -20 to 20. The result shows that the closer it is to the event day, the larger the correlation coefficients are. This pattern is very similar to the pattern of the average abnormal returns of intense institutional trading from day -20 to 20 (see Figure 5.1.1). The Spearman's rank correlation test confirms that institutions engage in herding and/or order splitting.

Figure 5.3 Average rank correlation coefficient from day -20 to 20
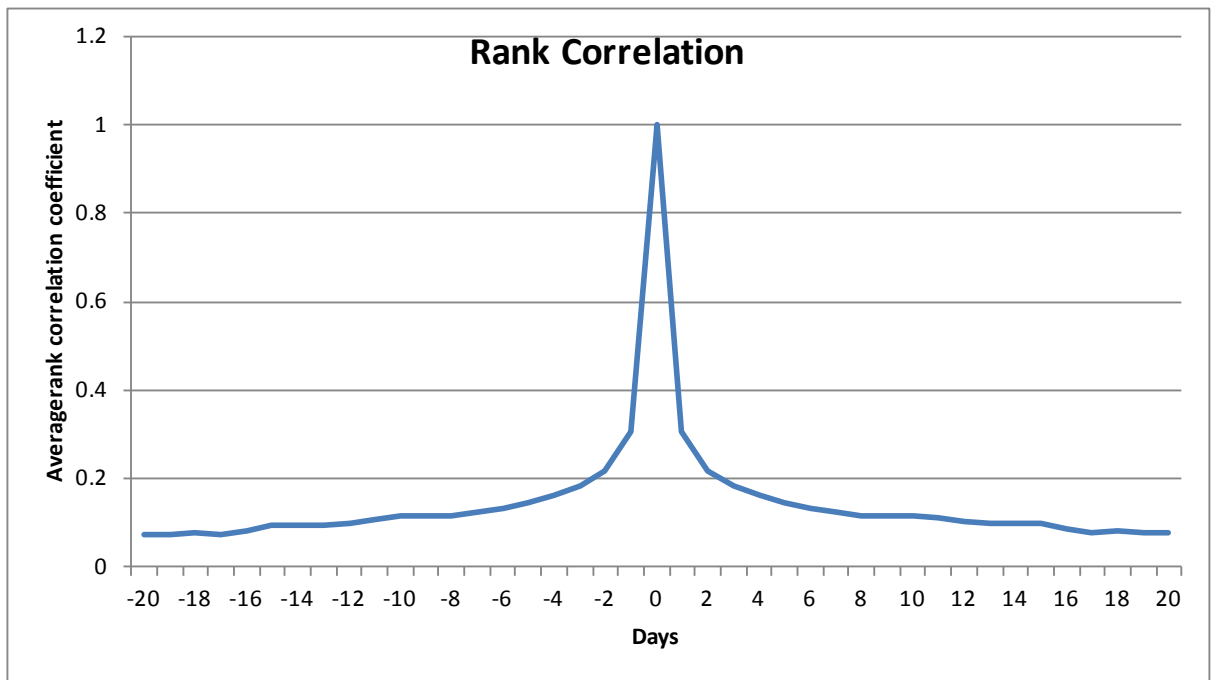
5.2 Daily Individual Trading and Stock Returns

### 5.2.1 Contemporaneous relation

The previous section shows that institutional trading has a positive impact on stock prices on the ranking day. For that reason, I hypothesise that individual trading also has a positive impact on the stock prices. I thereby expect the abnormal returns of the decile 1 to 1D to be significantly positive, but the decile 10 to 10D to be significantly negative on the ranking day.

From Table 5.2, the decile 1 stocks experience abnormal return of -0.45%, whereas the decile 10 stocks experience abnormal return of 1.24% on the ranking day, and both are statistically significant. The difference between the decile 10 and the decile 1 is 1.69% and is highly statistically significant. The abnormal returns for the decile 10A, 10B, 10C, and 10D are 0.62%, 0.90%, 1.26% and 2.19%, respectively, and are all statistically significant. In contrast, the abnormal returns of the intense individual buying portfolios exhibit an inverse pattern but with smaller magnitude. Specifically, the abnormal returns for the decile 1A, 1B, 1C and 1D are -0.52%, -0.50%, -0.40% and -0.37, respectively, and are statistically significant. The results suggest that there is a strong negative contemporaneous relation between individual trading and returns, that is, prices increase when individual investors sell shares but decline when they buy shares. This result is consistent with the finding of Kaniel et al. (2008). Thus, I reject my hypothesis that intense individual trading has a positive impact on stock prices.

Recall from the above that intense institutional buying pushes the prices up, whereas intense institutional selling pushes the prices down on the ranking day, and that the overall individual trading exhibits a pattern opposite to that of institutional trading, the visual evidence can be clearly seen in Figure 5.2.1. This might happen as individuals buy shares when selling pressure from institutions pushes prices down and sell shares when buying pressure from institutions pushes prices up. This pattern suggests that individuals trade with institutional investors, which mean that they buy stocks from, or sell stocks to institutions. To confirm this hypothesis, I find the correlation between the most intensely bought and sold stocks by institutions and individuals is -0.88, which confirms that individual trade with institutional investors by taking opposite position.

In sum, intense individual trading is negatively correlated with contemporaneous returns, and also negatively correlated with institutional trading. I find strong evidence that individuals trade with institutions, prices increase when individuals sell shares to institutions but decline when individuals buy shares from institutions.

Figure 5.2.1 the Daily Abnormal Returns around Individual Trading
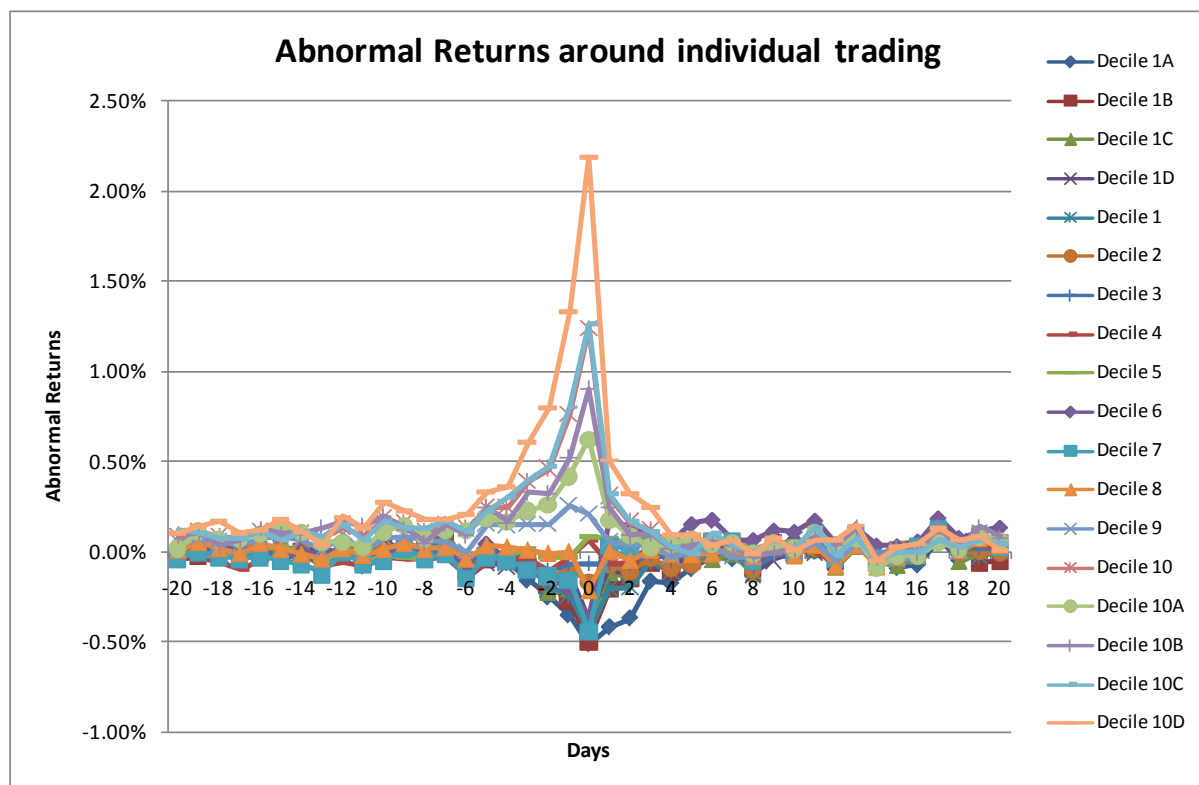
Note: the graph shows the daily market adjusted abnormal returns for portfolios sorted by daily change in individual ownership from day -20 to day 20. The sample period is from 1st June 2007 to 31st December 2008. Each trading day, I divide all stocks based on daily change in individual ownership and form 10 equal-weighted deciles and 8 sub-deciles. Decile 1 contains stocks that have intense individual buying activity and decile 10 contains stocks that have intense individual selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample.

5.2.2 Subsequent returns after intense individual trading

The poor performance of individual investors documented by Odean (1998, 1999) and Barber and Odean (2000) suggest that individual trading should be negatively correlated with subsequent returns. In other words, the stocks individual sell outperform those they buy. I test this hypothesis by examining the subsequent returns CARs (1, 20). If individual trading has negative predictive power, I expect the CARs (1, 20) to be significantly positive for the intense selling portfolios, but significantly negative for the intense buying portfolios. If individual trading has no predictive power, then I expect the CARs (1, 20) to be insignificant.

From Table 5.2, it can be seen that only the decile 10D stocks earn significant CARs of 1.91% 20 days following the ranking day and the CARs (1, 20) are statistically insignificant for other deciles. The difference between the decile 10D and the decile 1A is 3.39%, and is statistically significant. This suggests that stocks intensely sold by individuals outperform those they intensely bought, and the visual evidence can be seen from Figure 5.2.2. This finding allows us to make profit by constructing a simple long-short trading strategy: at the beginning of each trading day, I invest 1/20 of my fund to buy decile 10D stocks and short sale deciles 1A stocks and hold them for 20 days (based on one day lag change in individual ownership). By repeating this exercise every day for 20 days, and then I can make a profit of 3.39% by the end of the 20th day. By rolling this strategy forward, I can get a profit of 40.68% per annum (3.39% x 12 = 40.68%).

Similar to the analysis of institutional trading, I divide the CAR (1, 20) into CAR (1, 5) and CAR (6, 20) for further investigation. From Table 5.2, The CAR (1, 5) for the decile 1A, the decile 10D and the decile 10 are -1.23%, 1.23% and 0.68%, respectively, and are all statistically significant. The CARs (1, 5) are statistically insignificant for other deciles. The CARs (6, 20) are statistically insignificant for all the deciles; however, the difference between the decile 10D and the decile 1A is 0.93%, and is statistically significant. These results suggest that stocks intensely sold by individual outperform those they intensely bought from day 6 to 20, and the visual evidence can be clearly seen from Figure 5.2.2 and Figure 5.2.3.

Table 5.2 Individual Trading and Stock Returns

Decile	RAW(t=0)	AR (t=0)	CAR (1, 20)	CAR (1, 5)	CAR (6, 20)	CAR (-1, -20)	CAR (-1, -5)	CAR (-6 ,-20)
1A	-0.72***	-0.52***	-1.49	-1.23***	-0.23	-1.01	-0.81	-0.2
	-3.26	*-2.67*	*-1.45*	*-2.59*	*-0.28*	*-0.97*	*-1.61*	*-0.24*
1B	-0.7***	-0.5***	-0.73	-0.59	-0.14	-0.76	-0.66	-0.1
	-3.58	*-2.61*	*-0.74*	*-1.31*	*-0.18*	*-0.79*	*-1.47*	*-0.13*
1C	-0.6***	-0.4**	-0.56	-0.29	-0.27	-0.41	-0.5	0.09
	-3.07	*-2.07*	*-0.59*	*-0.69*	*-0.35*	*-0.45*	*-1.12*	*0.12*
1D	-0.57***	-0.37*	-0.35	-0.4	0.05	-0.6	-0.46	-0.14
	-3.13	*-1.94*	*-0.37*	*-0.95*	*0.07*	*-0.62*	*-1.01*	*-0.18*
1	-0.65***	-0.45**	-0.77	-0.62	-0.15	-0.69	-0.61	-0.09
	-3.32	*-2.36*	*-0.8*	*-1.43*	*-0.19*	*-0.72*	*-1.33*	*-0.12*
2	-0.37**	-0.17	-0.32	-0.38	0.07	-0.32	-0.33	0.01
	-2.12	*-0.88*	*-0.33*	*-0.88*	*0.09*	*-0.33*	*-0.74*	*0.01*
3	-0.27	-0.07	-0.2	-0.21	0.1	-0.58	-0.27	-0.31
	-1.57	*-0.36*	*-0.2*	*-0.45*	*0.09*	*-0.56*	*-0.59*	*-0.36*
4	-0.14	0.06	0.06	-0.11	0.17	-1.02	-0.27	-0.75
	-0.9	*0.34*	*0.06*	*-0.23*	*0.19*	*-0.95*	*-0.6*	*-0.82*
5	-0.12	0.08	0.88	0.24	0.64	-0.48	-0.1	-0.38
	-0.91	*0.47*	*0.89*	*0.55*	*0.8*	*-0.46*	*-0.22*	*-0.46*
6	-0.27	-0.07	0.75	0.28	0.35	-0.68	-0.46	-0.22
	-1.61	*0.98*	*0.71*	*0.36*	*0.39*	*-0.65*	*-1.06*	*-0.26*
7	-0.44**	-0.24	0.62	0.18	0.45	-1.2	-0.47	-0.73
	-2.75	*-1.38*	*0.61*	*0.38*	*0.53*	*-1.06*	*-0.98*	*-0.79*
8	-0.42**	-0.22	-0.02	-0.07	0.05	0.16	0.05	0.1
	-2.45	*-1.15*	*-0.02*	*-0.16*	*0.06*	*0.14*	*0.11*	*0.11*
9	0.01	0.21	0.22	0.11	0.11	1.7	0.86**	0.84
	0.057	*1.15*	*0.24*	*0.28*	*0.14*	*1.7*	*2.01*	*1.02*
10	1.04***	1.24***	1.27	0.68*	0.59	3.83***	2.1***	1.73**
	5.99	*6.86*	*1.5*	*1.78*	*0.85*	*3.95*	*4.98*	*2.22*
10A	0.42***	0.62***	0.87	0.41	0.46	2.6***	1.27***	1.33*
	5.55	*3.42*	*1.01*	*1.06*	*0.65*	*2.72*	*2.99*	*1.74*
10B	0.7***	0.9***	1.18	0.49	0.69	3.27***	1.58***	1.68**
	4.07	*4.93*	*1.36*	*1.24*	*0.98*	*3.38*	*3.72*	*2.13*
10C	1.06***	1.26***	1.15	0.61	0.54	3.85***	2.2***	1.65**
	6.12	*6.93*	*1.38*	*1.58*	*0.79*	*3.92*	*5.19*	*2.13*
10D	1.99***	2.19***	1.91**	1.23***	0.68	5.68***	3.4***	2.28**
	10.18	*11.68*	*2.19*	*3.09*	*0.92*	*5.42*	*7.46*	*2.73*
1-10	-1.68***	-1.68***	-2.05***	-1.3***	-0.74**	-4.53***	-2.7***	-1.82***
	-21.4	*-21.4*	*-6.48*	*-7.83*	*-2.75*	*-13.26*	*-14.58*	*-7.47*
1A-10D	-2.7***	-2.7***	-3.39***	-2.46***	-0.93***	-6.69***	-2.47***	2.47***
	-21.68	*-21.68*	*-7.32*	*-10.31*	*2.41*	*-14.18*	*-6.91*	*-6.91*

Notes: Table 5.2 presents abnormal returns and various periods' cumulative abnormal returns around intense individual trading. The sample period is from 1st June 2007 to 31st December 2008. Each trading day, I divide all stocks based on daily change in individual ownership and form equal-weighted 10 deciles and 8 sub-deciles. Decile 1 contains stocks that have intense individual buying activity; Decile 10 contains stocks that have intense individual selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample. Numbers in italic are Newey-West *t-statistics* *** Significant at 1% level   ** Significant at 5% level * Significant at 10% level. All figures are in percentage.

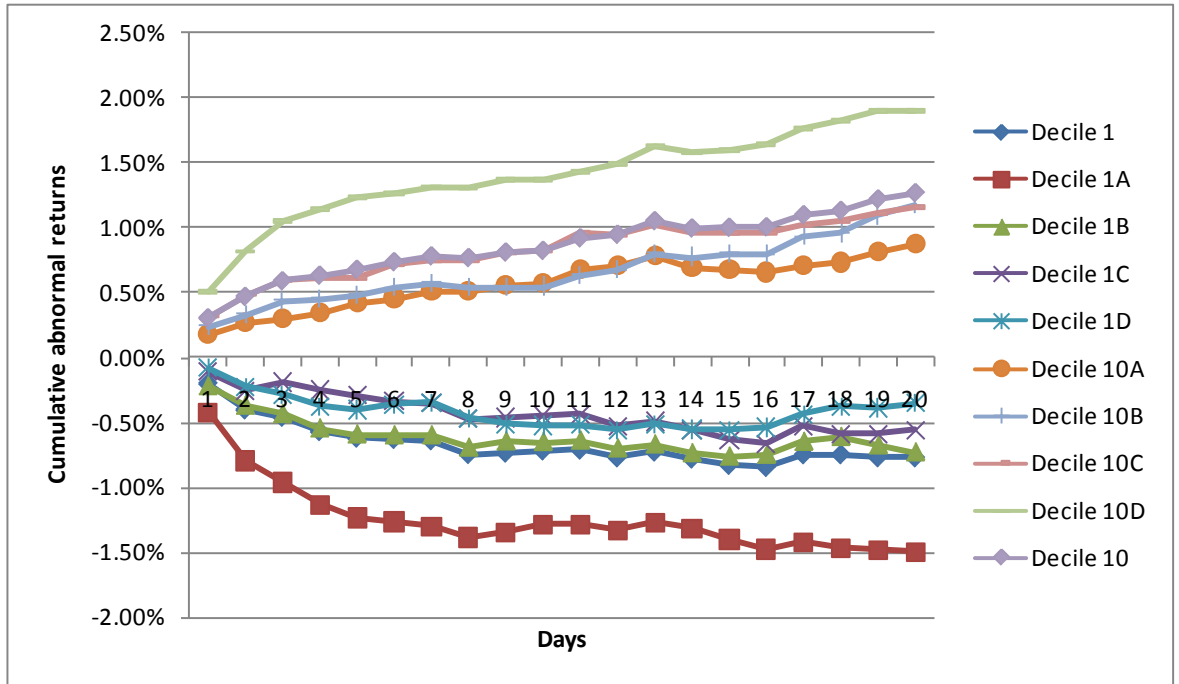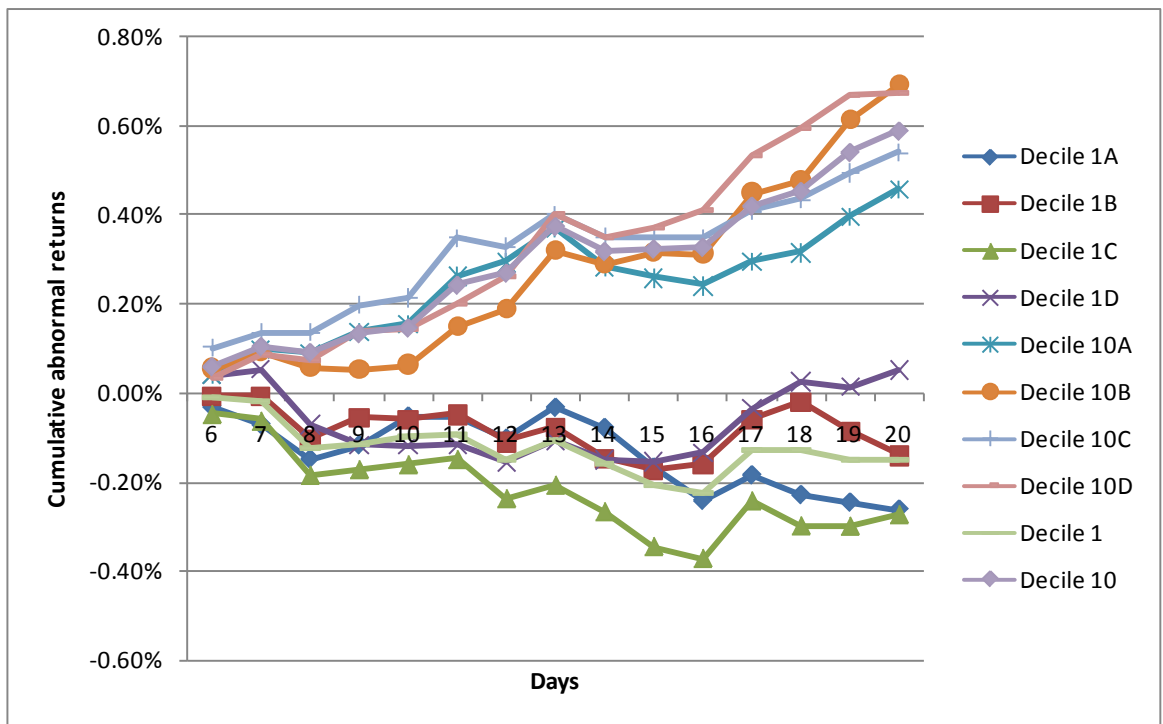**Figure 5.2.2 Cumulative Abnormal Returns from day 1 to 20 - Individual**

Figure 5.2.3 Cumulative Abnormal Returns from day 6 to 20 - Individual

Note: Each trading day from 1st June 2007 to 31st December 2008, I divide all stocks based on daily change in individual ownership and form equal-weighted 10 deciles and 8 sub-deciles. Decile 1 contains stocks that have intense individual buying activity; Decile 10 contains stocks that have intense individual selling activity. The abnormal return on each portfolio is calculated by subtracting the return on the equal-weighted portfolio of all stocks in the sample.

The result shows that intense individual selling is negatively correlated with subsequent returns suggesting that individual selling has negative predictive power, that is, individual investors perform poorly. This is consistent with the finding of Odean (1998, 1999) and Barber and Odean (2000). In contrast, this result contradicts the finding of Kaniel et al. (2008) and Jackson (2003), who found good performance of individual investors. More, this result also contradicts to the finding of Ng and Wu (2007) and Griffin et al. (2003), suggesting that individual trading cannot predict future returns.

In sum, I find that intense individual selling is negatively correlated with the subsequent returns, that is, stock intensely sold by individual outperform those they intensely bought.

5.2.3 Returns prior to individual trading

Recent studies document that individuals are contrarian traders (Kaniel et al., 2008), that is, they buy past loser stocks and sell past winner stocks. If individual investors are contrarian traders, I expect intense individual trading to be negatively correlated with prior returns (CAR -1, -20), i.e. the CARs (-1, -20) are significantly positive for the intense buying portfolios, but significantly negative for the intense selling portfolios. If the CARs (-1, -20) are insignificant for all the deciles, it suggests that individuals are neither momentum nor contrarian traders.

From Table 5.2, the CARs (-1, -20) are statistically insignificant for all the intense buying portfolios, but significantly positive for all the intense selling portfolios. Specifically, the CARs (-1, -20) for decile 10 to 10D are 3.83%, 2.6%, 3.27%, 3.85% and 5.68%, respectively, and are statistically significant at the 1% level. The CARs (-1, -20) for decile 1 to 1D are all statistically insignificant. The result shows that individuals are contrarian traders for selling but not for buying.

Similar to the analysis of institutional trading, I also divide the CAR (-1, -20) into the CAR (-1, -5) and the CAR (-6, -20) for further investigation. From Table 5.2, both CAR (-1, -5) and CAR (-6, -20) show the same result as CAR (-1, -20), suggesting that individuals are contrarian traders for selling but not for buying. The result is partly consistent with recent studies which document that individual investors are contrarian traders for both buys and sells (Odean, 1998; Barber and Odean, 2000; Griffin et al.,

2003; Kaniel et al., 2008; Choe et al., 1999; Ng and Wu, 2007). In sum, I find that individuals are contrarian traders for selling but not for buying.

Chapter 6

Conclusion

The institutional ownership and institutional trading activity in China have increased dramatically over the last decade. This dissertation examines the impact of institutional (and individual) trading on stock prices in China. Previous literature suggests three alternative hypotheses for this impact: price pressure, informed trading, and momentum trading, but has so far not been able to distinguish between them. Using a unique dataset that contains detailed daily institutional and individual ownership information for all Shanghai Stock Exchange stocks in China, I am able to examine the important relation between daily aggregate institutional and individual trading and past, contemporaneous, and future stock returns at a daily level.

I find strong evidence of the price pressure effect induced by institutional trading. Institutions are informed traders and momentum traders for buying but not for selling. Moreover, I find strong evidence that individuals trade with institutions by taking the opposite position, which can largely explain the opposite results found for individual trading. My findings have important implications. First, the finding that institutions are informed traders is important for regulators and exchange officials who are concerned with promoting the transparency of information. Second, momentum trading and price pressure effects can cause stock prices to deviate from their fundamental level, which destabilises the financial market, and reduce its efficiency. Finally, individuals suffer losses from trading with institutions. Individual investors should therefore let institutions manage their funds. Otherwise, individual investors can profit by mimicking institutional trading.

Given a relatively short period of daily ownership data, I cannot examine the long-term effect of institutional and individual trading and stock returns. Hence, I only focus on short-horizon return patterns. In addition, I focus on the aggregate institutional activity and do not separately investigate different type of institutional investors, such as: mutual funds, insurance companies, banks, and investment advisors. Different institutional investors may indeed have different trading strategies (Yan and Zhang, 2009).

I suggest three avenues for future research. First, future research could study different institutional types and their impact on stock prices as in this dissertation focuses on aggregate institutional trading. Second, recent studies document that institutional trading generate excess volatility [13], we can investigate institutional trading in the context of the volatility of stock market. Finally, I find the significant portion of abnormal returns few days immediately before and after institutional trading is due to price pressure effect induced by herding and/or order splitting. However, this effect cannot be eliminated in calculating the abnormal returns in this study. Future research may find a better methodology to eliminate the price pressure effect so that we can get abnormal returns that purely relates to information.

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[13] Gabaix ,Gopikrishnan ,Plerou , and Stanley (2006) present a theory of market volatility where institutional trades generate produce excessive price movements.

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