THREE ESSAYS IN BEHAVIORAL FINANCE

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THREE ESSAYS IN BEHAVIORAL FINANCE

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In Chapter 1, we study the trading pattern of rich individual investors. To the contrary of the current literature that individual investors trade excessively, and that trading is hazardous to their wealth, we find that in the Chinese stock market, individual investors with stock holdings over 5 million RMB benefit from trading. Our results show that these super rich individual investors trade far more extensively than the market average. Yet they manage to beat the performance of the market portfolio in China by a large margin. Further investigation attributes their persistent excess returns to informational advantages. We find evidence that they trade against behavioral investors around good news announcements.

In Chapter 2, we study a puzzling phenomenon in the Chinese stock market, that is a stock's price and its trading volume rise significantly after public news, unrelated to a concrete change in the firm's value. We propose a model of trade-based manipulation to explain this phenomenon. In this model, a large number of speculative manipulators coordinate implicitly after public news events to exploit investors with behavioral biases. We provide empirical evidence that is consistent with the prediction of the model. Stocks that have low institutional investor holdings or that have experienced a recent decline in value are more likely to be manipulated. Manipulated stocks experience price reversals after the manipulation. We suspect that speculative manipulators are investors with more than five million RMB in stocks' value. These

investors accumulate shares to pump up the stock price initially and then dump them after the significant increase in price. Their accounts also realize abnormally high returns during the event days.

In Chapter 3, we study the cross-sectional differences in IPO pricing under sentiment and disagreement influences in the Chinese stock market. We find that the first-day returns of IPOs are positively related to market sentiment and disagreement over their offer prices. Hard-to-value IPO stocks earn higher first-day returns when investor sentiment is higher. Issuers in the Chinese stock market are not able to time the market for regulatory reasons, making our results less affected by the endogenous issue between market sentiment and IPO underpricing observed in the US market. A unique data set containing analysts’ forecasts about IPO offer prices allows us to measure the disagreement over the IPO valuations directly, which is also not available for the US market.

BIOGRAPHICAL SKETCH

Ziyang Geng was born and raised in Nanjing, China. In 1998, he graduated from high school and entered Nanjing University with major in Accounting. After receiving his B.A. in Accounting in 2002, Ziyang came to US and enrolled in the M.A. program in accounting at Abilene Christian University. In 2004, he obtained his M.A. degree in Accounting and was admitted to the Ph.D. program at Cornell University in the field of Economics. His research interests are behavioral finance and empirical asset pricing. His projects mainly focus on the investment performances of individual investors.

Ziyang Geng worked as an auditor at Deloitte & Touche LLP during 2006-2009 and holds a CPA license.

For my parents: Naifan Geng and Junping Guan.

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CHAPTER 1

IS TRADING HAZARDOUS TO YOUR WEALTH?

The literature on behavioral finance finds that individual investors lose from trading. Using data from a discount brokerage, Barber and Odean (2000) show that individual investors trade excessively (overtrading), and they underperform the index by 3.7% annually. Further, Barber et al. (2009) directly measure how much individual investors lose from trading by using data from the Taiwan market and find that individual investors suffer an annual performance penalty of 3.8%. Similarly, Han and Kumar (2011) find that stocks actively traded by individual investors have a negative alpha.

However, the literature also shows that some individual investors can profit from trading because of an information advantage or skill. Ivkovic and Weisbenner (2005) find that individual investors who hold local stocks do better. Later on, Ivkovic et al. (2008) find that individuals who hold one or two stocks do better than those who hold at least three stocks. These authors attribute individual investors' performance to an informational advantage. Coval et al. (2005) find that those investors who hold winning stocks do better. They believe these investors have extraordinary stock picking ability, that is, skill.

Thus, apparently, there is no consensus for trading's effect on individual investors' wealth, yet all individual investors expect to profit from trading. We use a new data set on individual investors' trading and holding records from a national brokerage firm in China to study whether trading is hazardous to individual investors' wealth. This unique data set contains daily position statements and trading records for 1.8 million individual investors from 2007 to 2009.

Previous studies shed light on which stocks winning individual investors buy (Ivkovic and Weisbenner (2005), Ivkovic et al. (2008), and Coval et al. (2005)). Another line of papers focuses on the roles of gender, income, age, and education in individual investors' performance.[1] We are interested in the role of investors' wealth in their investment performance. Specifically, do less wealthy investors become richer through trading? Does trading hurt rich investors' wealth?

In this paper, we attempt to answer these questions by partitioning individual investors by the value of their portfolio, which approximates the level of wealth of the individual investors. When reporting individual investors' statistics, the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE) label accounts with less than 100,000 RMB in equity at any point in time as small accounts, those with less than 1,000,000 RMB as middle accounts, those with less than 5,000,000 RMB as big accounts, and those with more than 5,000,000 RMB as super accounts. We follow this practice in our paper as well. Therefore, we classify individuals as small, middle, big, and super investors based on their portfolio size.

For small, middle, and big investors, we find that trading is hazardous to their wealth, confirming Barber and Odean (2000). All of these investors earn significantly negative returns after factoring in the trading costs. Also with the increase in trading frequency, as

[1] Barber and Odean (2001) find that women outperform men by 0.93 percentage points a year by comparing the net returns they earn. Kumar (2009) considers the characteristics of individual investors, including income, age, and education, to explain individual investors' preference for lottery-like stocks, which earn significantly lower average returns than non-lottery-like stocks.

indicated by a portfolio's turnover, the net returns earned by these three groups of investors decrease monotonically.

But for super investors, we find, in contrast to Barber and Odean (2000), that trading increases their wealth. During our sample period, super investors achieve monthly average excess gross (net) returns of 10% (8%) at the 5% significance level.

Barber and Odean (2000) also partition their investors into quintiles on the basis of portfolio size. However, they find that investors holding small portfolios earn higher average returns than those who hold large portfolios. They attribute the difference to the outperformance of small value stocks during their sample period. We do not find that small value stocks or big value stocks do particular well during our sample period. Moreover, the mean price difference of stocks traded by small investors and that by super investors is merely 4 RMB, which is approximately 57 cents in US dollars. This difference is not sufficient to explain why the super investors beat the small investors by such a large margin.

Furthermore, we find that the more super investors trade, the higher the returns (both gross and net) that they get (see Figure 1). This empirical evidence is the most surprising and contradicts the literature.

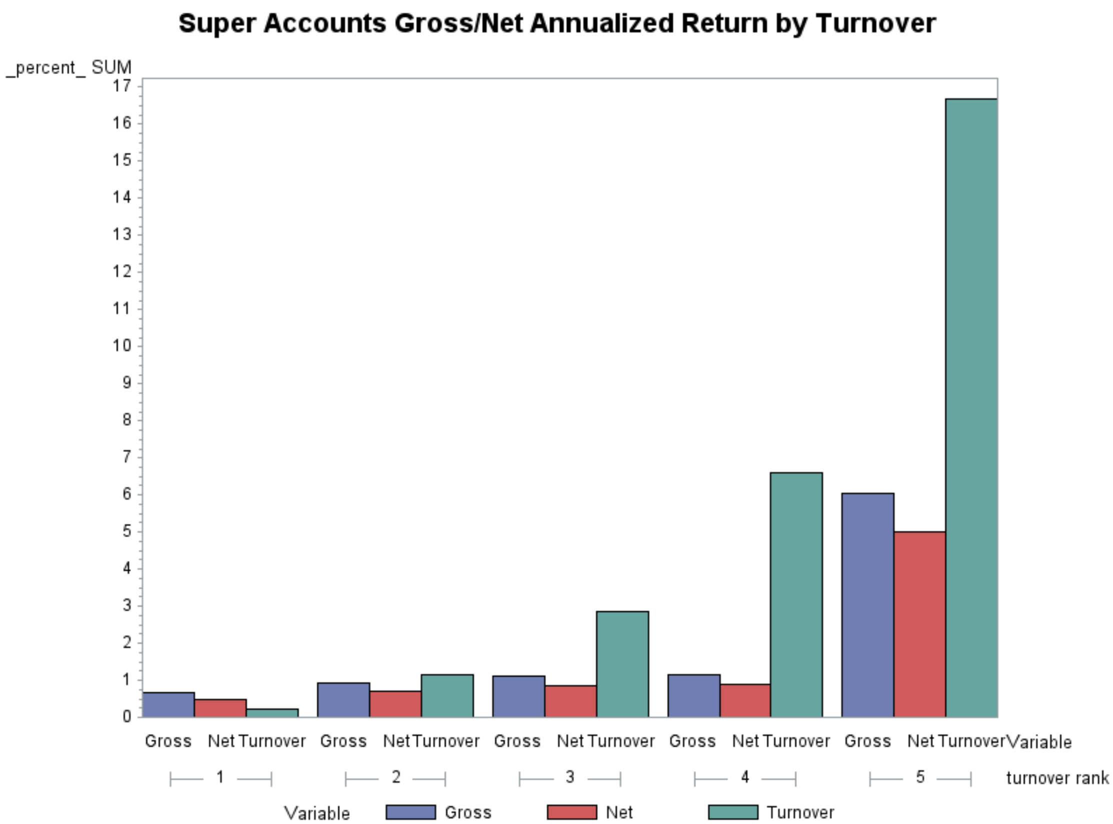

FIGURE 1 RELATION BETWEEN TURNOVER AND RETURNS FOR SUPER INVESTORS

We divide super accounts investors into quintiles by turnover. Turnovers are measured monthly by summing the sale turnover and buy turnover. Gross returns are measured monthly and net returns are calculated by subtracting trading costs. It turns out that high turnover brings high returns for wealthy investors.

In this paper, we show that an informational advantage is a possible source of super investors' superior performance. We perform an event study and find that the trading of local stocks with announcements of high stock dividends is dominant among super investors. And they profit from buying these stocks before the announcement and selling them afterwards.

In contrast to Ivkovic and Weisbenner's (2005) finding that investors who hold local stock do better, we find that only super investors that hold local stocks do better. The other three groups of investors do not benefit from holding local stocks. These groups probably suffer from local biases.

Moreover, Ivkovic et al. (2008) find that investors who hold local stocks and small portfolios have lower turnover. In this sense, they support Barber and Odean (2000) by finding that turnover is negatively related to returns. We find that higher turnover brings higher returns for super investors.

Compared to the current research, our contributions are as follows. Firstly, we attempt to differentiate investors based on their wealth and find that trading benefits super investors but hurts the small, medium, and big investors. In fact, we find that super investors get richer through trading, while the other investors lose from trading. The research often assumes the homogeneity among investors. In other words, they treat investors as a whole without recognizing the difference between each investor.

Secondly, we complement the literature on information advantage with data at the investor account level. On the information leakage side, there are many papers that use stock-level data such as abnormal returns, abnormal volatilities, abnormal turnovers, and short sale interests. However, these papers lack a direct measure of how people who have an informational advantage trade on that information.

Thirdly, we extend the understanding of the Chinese stock market, which had 120 million investment accounts at year-end 2009 (China Securities Regulatory Commission (2009)). The Chinese market also had the second-largest market capitalization among all national stock markets at year-end 2010. Chen et al. (2007) and Feng and Seasholes (2008) both find that Chinese investors exhibit excessive trading because of the disposition effect, local bias, and under-diversification; just as retail investors in the US do. Our paper finds that super, high frequency trading, investors in the Chinese stock market profit from trading and beat the market, which is not true for US investors.

The remainder of the paper is organized as follows: Section I provides a description of the main data set we use for this research. Section II analyses the trading performance of all groups of investors. Section III presents an event study to explore the source superior performance of super investors. Section IV concludes.

I. Data Description

Our data on trading and daily portfolio holdings come from a top brokerage firm in China. The trading data contains 1.8 million investors' trading records from January 2007 to October 2009.[2] Our data set contains investors that trade common stocks, funds, treasury

[2] Many papers studying the trading patterns of individual investors in the US market that are based on the data set examined in Barber and Odean (2000). Their data set contains information from a large discount brokerage firm on the investments of 78,000 households from January 1991 through December 1994. Therefore, our data is newer and bigger compared to the data used in Barber

notes, and warrants. In this paper, we focus only on their trading of common stocks, which is about 80% of all trading records.

There are two stock exchanges in Mainland China, the Shanghai Stock Exchange (SHSE) and the Shenzhen Stock Exchange (SZSE). By the end of 2009, the 2,000 stocks traded on the SHSE and the SZSE had a combined total market capitalization of US$ 3.5 trillion, making the Chinese stock market one of the largest in the world. To trade on the SHSE and the SZSE, investors can open one and only one permanent stock account with each exchange. Even if an investor decides to close his or her account with an exchange, the stock account's number is not recycled for future investors. This institutional setup allows us to track investors' performance consistently over our sample period. Therefore, our results are free of survivorship bias. Also, as mentioned, we use the same cutoffs as the exchanges for the values of portfolios to classify the investors.

To eliminate the bias caused by inactive investors in our sample, we exclude investors who bought or sold shares less than 20 times during our sample period. Panel A in Table 1 shows the distribution of the number of investors in each category. We find that inactive accounts are limited in the small and middle groups of investors.

Panel A in Table 1 also presents a comparison of the investors' distribution by their holdings between our data set and the entire market. In the overall market, over 80% of the investors are small accounts, middle accounts are 15%, and only a tiny fraction of investors holds more than 1 million RMB. Our data set has a more balanced distribution

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and Odean (2000). More importantly, the daily position data, instead of the month-end position data, allow us to calculate returns more accurately.

between small and middle accounts, 52% versus 42%. The fractions of big and super accounts are close to the market average.

Our sample period covers a turn from the bull market (2007) to the bear market (2008). The values of the investors' portfolios also change with this market fluctuation. Panel B in Table 1 shows the mean portfolio size for different types of investors at each year-end for 2007, 2008, and 2009. The small and middle investors took the biggest hits with an average 42% loss in the values of their holdings during 2008. The super investors did a better job in managing their portfolios in the bear market with an average loss of 25%.

TABLE 1 ACCOUNTS DISTRIBUTION

Active accounts are investors who bought or sold shares at least 20 times during our sample period, January 2007-Octorber 2009. Small accounts are investors with portfolio worth less than 100,000 RMB at any point, Middle accounts are investors with portfolio worth less than 1,000,000 RMB at any point, Big accounts are investors with portfolio worth less than 5,000,000 RMB at any point, Super accounts are investors with portfolio worth more than 5,000,000 RMB at any point. Market statistics are from Shanghai Stock Exchange (SHSE) fact book for year 2008 and 2009.

Panel A: Number of Accounts Distribution

Accounts	Active	Active (%)	Total	Total (%)	2008 SHSE (%)	2009 SHSE (%)
Small	529970	52.98	1104325	65.96	91.97	82.78
Middle	419975	41.98	519476	31.03	7.62	15.99
Big	44353	4.43	44353	2.65	0.36	1.1
Super	6028	0.60	6028	0.36	0.05	0.12

Panel B: Size of Accounts Distribution

Account	Mean (2007)	Mean (2008)	Change (%)	Mean (2009)	Change (%)
Small	9,641.92	5,635.51	41.5	10,013.78	77.7
Middle	45,962.31	25,293.34	44.9	45,038.07	78.1
Big	297,679.96	154,783.97	48.0	273,367.32	77.1
Super	4,087,718.26	3,046,965.60	25.4	5,641,246.56	85.1

Panels A and B in Table 2 report the means and medians of the trade size, average price, monthly turnover, and commission costs for buy and sell transactions separately. For each group of investors, there are slightly more purchases then sales during the sample period, although the average value of the stocks sold is slightly higher than the value of the stocks bought. The average purchase costs of small, middle, and big accounts are higher than the average sale prices of the corresponding accounts. However, for super accounts, the average sell price is slightly higher than the average purchase cost.

TABLE 2.A SUMMARY STATISTICS FOR BUY TRANSACTIONS

The sample is account records for 1.8 million individual investors at a national brokerage firm from January 2007 to October 2009. Small accounts are investors with portfolio worth less than 100,000 RMB at any point, Middle accounts are investors with portfolio worth less than 1,000,000 RMB at any point, Big accounts are investors with portfolio worth less than 5,000,000 RMB at any point, Super accounts are investors with portfolio worth more than 5,000,000 RMB at any point. Monthly turnover is the total trade value divided by average portfolio size. Commission is calculated as the commission paid divided by the value of the trade.

	Small	Middle	Big	Super
Panel A: Trade Size (RMB)				
Mean	6,158	18,733	67,321	237,815
25^{th} Percentile	1,995	4,340	11,075	33,550
Median	3,860	8,950	28,590	92,200
75^{th} Percentile	7,350	19,560	72,120	234,800
Std. Dev.	7,427	32,694	126,337	683,328
# of Obs.	44,930,409	72,432,032	11,700,368	2,644,357
Panel B: Price/share				
Mean	12.48	14.45	15.64	16.25
25^{th} Percentile	6.62	7.24	7.61	7.80
Median	9.68	10.90	11.64	11.97
75^{th} Percentile	15	17.16	18.50	19.06
Std. Dev.	9.77	12.22	13.82	14.62
# of Obs.	44,930,409	72,432,032	11,700,368	2,644,357
Panel C: Monthly Turnover(%)				
Mean	5.17	6.46	6.58	7.74
25^{th} Percentile	2.50	2.45	2.03	1.95
Median	3.73	3.96	3.76	3.89
75^{th} Percentile	5.95	6.82	7.10	7.89
Std. Dev.	6.04	12.17	11.75	18.56
# of Obs.	529,868	419,679	43,684	5,713
Panel D: Commission (%)				
Mean	0.45	0.36	0.27	0.22
25^{th} Percentile	0.28	0.21	0.12	0.08
Median	0.40	0.32	0.23	0.18
75^{th} Percentile	0.58	0.49	0.40	0.36
Std. Dev.	0.33	0.29	0.29	0.23
# of Obs.	44,930,409	72,432,032	11,700,368	2,644,357

Moreover, we calculate the monthly portfolio turnover for each investor. The monthly purchase turnover is calculated as the total value of shares bought during month *t* divided by the total beginning-of-the-month market value of the portfolio, which is the end-of-the-month value of month *t-1*. To calculate the monthly sales turnover, we divide the total value of shares sold during month *t* by the total end-of-the-month market value of the portfolio for month *t*. In Panel C of Table 2.A and Table 2.B, we report that small investors buy 5.17% and sell 5.20% of their stock portfolio each month, although super investors purchase 7.74% and sell 11.84% of their stock portfolio each month.

In sum, the trade size, average trade price, and monthly turnover increase with the investors' wealth level. The investors with higher budgets probably can afford more expensive stocks and trade more frequently.

TABLE 2.B SUMMARY STATISTICS FOR SALE TRANSACTIONS

The sample is account records for 1.8 million individual investors at a national brokerage firm from January 2007 to October 2009. Small accounts are investors with portfolio worth less than 100,000 RMB at any point, Middle accounts are investors with portfolio worth less than 1,000,000 RMB at any point, Big accounts are investors with portfolio worth less than 5,000,000 RMB at any point, Super accounts are investors with portfolio worth more than 5,000,000 RMB at any point. Monthly turnover is the total trade value divided by average portfolio size. Commission is calculated as the commission paid divided by the value of the trade.

	Small	Middle	Big	Super
Panel A: Trade Size (RMB)				
Mean	6,919	22,184	80,471	272,136
25th Percentile	2,915	4,970	12,890	40,122
Median	4,293	10,365	34,000	109,800
75th Percentile	8,305	23,560	86,700	278,772
Std. Dev.	8,267	37,963	146,513	615,292
# of Obs.	38,797,064	60,222,095	9,723,899	2,395,542
Panel B: Price/share				
Mean	12.33	14.21	15.47	16.36
25th Percentile	6.53	7.15	7.57	7.92
Median	9.53	10.75	11.56	12.17
75th Percentile	14.80	16.90	18.31	19.34
Std. Dev.	9.71	12.02	13.54	14.38
# of Obs.	38,797,064	60,222,095	9,723,899	2,395,542
Panel C: Monthly Turnover (%)				
Mean	5.20	6.75	8.36	11.84
25th Percentile	2.49	2.48	2.06	1.88
Median	3.70	3.96	3.77	3.81
75th Percentile	5.88	6.82	7.20	7.98
Std. Dev.	7.54	13.03	12.54	24.03
# of Obs.	529,913	419,891	44,018	5,963
Panel D: Commission (%)				
Mean	0.55	0.44	0.36	0.29
25th Percentile	0.35	0.28	0.20	0.16
Median	0.42	0.37	0.28	0.21
75th Percentile	0.57	0.48	0.40	0.36
Std. Dev.	1.85	1.65	1.63	1.29
# of Obs.	38,797,064	60,222,095	9,723,899	2,395,542

Following Barber and Odean (2000), we calculate the commission component of the transaction costs as the RMB value of the commission paid scaled by the total principal value of the transaction. We observe the decrease in commission costs as a percentage of the wealth level, which can be attributed to the lower commission fee charged by the broker to the super accounts.[3]

During the sample period, on average, investors hold no more than five stocks monthly, which is the least needed to diversify idiosyncratic risk. The stock holdings of small investors are even more concentrated with about three stocks each month (Table 3). Under-diversification of individual portfolios is not a new issue in the finance literature. The reason for such low diversification could be budget constraints, limited attention, local bias, and or skewness preference (Mitton and Vorkink (2007) and Kumar (2009)).

If we further adjust the average holdings by the values of the investors' portfolios, then we find that small investors hold three times more stocks than super investors (Table 3). Investors with over 5 million RMB in equity have enough funds to diversify their portfolios. Yet their portfolios are extremely under-diversified when conditioned on their portfolio sizes. Considering the high turnover of super accounts, the possibility exists that these investors are truly informed about valuable news that is related to the stocks they trade in.

We obtain stock returns, market capitalizations, Fama and French's three factors, and accounting data from the China Stock Market & Accounting Research Database (CSMAR).

[3] To keep wealthy investors from moving to other brokerages, it is common to discount the commission for investors who trade frequently. For each sell trade, investors pay a handling fee, commission, and a stamp tax. If buying stocks, investors need to pay the handling fee and commission only. The handling fee is collected by exchanges, the commission is collected by brokers, and the stamp tax is collected by Treasury Department.

TABLE 3 AVERAGE MONTHLY HOLDINGS OF INDIVIDUAL INVESTORS

This table presents number of stocks held by investors on average. Small accounts are investors with portfolio worth less than 100,000 RMB at any point, Middle accounts are investors with portfolio worth less than 1,000,000 RMB at any point, Big accounts are investors with portfolio worth less than 5,000,000 RMB at any point, Super accounts are investors with portfolio worth more than 5,000,000 RMB at any point. To control for the wealth level of different accounts, number of stocks are divided by average portfolio size.

	Average Number of Stock Holding	Wealth Adjust number of Stock Holding
Small	2.68	0.00139
Middle	4.01	0.00093
Big	5.06	0.00061
Super	5.00	0.00053

II. Return Performance

A. Methods and Variable Definition

We analyze the return performance of investments in common stocks according to their position value. Following Barber and Odean (2000), we calculate both the gross and net returns for each group of investors. Leveraging on the daily portfolio data, we are able to calculate the daily returns then compound those into monthly returns.[4] To mitigate the impact of the market fluctuation in the sample period, we also calculate the risk-adjusted excess returns for comparison.

To consider the common stock portfolio of a particular investor, we calculate the gross daily return on his or her portfolio (R_{ht}^{gr}) as

$$R_{ht}^{gr} = \sum_{i=1}^{S_{ht}} p_{it} R_{it}^{gr},$$

where p_{it} is the previous day's market value for the holding of stock i by investor h on day t divided by the previous day's market value of all stocks held by investor h, R_{it}^{gr} is

[4] Due to the availability of only monthly portfolio statements, Barber and Odean (2000) calculate the monthly return with two assumptions, one is that all transactions occur on the last day of the month. The other is that there is no intra-month trading. We do not have to make these two assumptions, because our data set provides daily portfolio statements for each individual investor.

the gross daily return for stock i, and S_{ht} is the number of stocks held by investor h on day t. Then we calculate the gross monthly return (CR_{ht}^{gr}) by compounding the daily return.

Similar to Barber and Odean (2000), we calculate a daily return net of transaction costs (R_{it}^{net}) as

$$(1 + R_{it}^{net}) = (1 + R_{it}^{gr}) \frac{(1 - c_{it}^{s})}{(1 + c_{i,t-1}^{b})},$$

where c_{it}^{s} is the cost of sales divided by the sales price on day t , and $c_{i,t-1}^{b}$ is the cost of purchases divided by the purchase cost on day $t - 1$. The costs of purchases and sales are calculated for each trade, including the commissions. The net daily portfolio return for each investor is

$$R_{ht}^{net} = \sum_{i=1}^{S_{ht}} p_{it} R_{it}^{net}.$$

The net monthly return (CR_{ht}^{net}) is calculated by compounding the net daily return. We estimate the gross and net monthly returns obtained by individual investors as

$$RI_{t}^{gr} = \frac{1}{n_{ht}} \sum_{h=1}^{n_{ht}} CR_{ht}^{gr} \text{ and } RI_{t}^{net} = \frac{1}{n_{ht}} \sum_{h=1}^{n_{ht}} CR_{ht}^{net},$$

where n_{ht} is the number of individual investors holding stocks in month t.

Furthermore, we calculate three measures of risk-adjusted performance: the market-adjusted abnormal return, the abnormal return estimated from the CAPM, and the abnormal return estimated from Fama and French’s (1993) three-factor model.

First, the mean monthly market-adjusted abnormal return of the individual investors is calculated as the difference between the returns earned by individual investors and the returns on a value-weighted index of stocks traded on the SHSE and the SZSE.

Second, we calculate the intercept using the CAPM model. We perform the regression of the monthly excess returns obtained by individual investors on the market excess return to approximate the abnormal return. For instance, to evaluate the gross monthly return obtained by individual investors on average, we estimate the following monthly time-series regression:

$$\left(RI_t^{gr} - R_{ft}\right) = \alpha_i + \beta_i\left(R_{mt} - R_{ft}\right) + \epsilon_{it},$$

where R_{ft} is the monthly risk-free rate, R_{mt} is the monthly return on a value-weighted market index, α_i is the CAPM intercept, β_i is the market beta, and ϵ_i is the error term. We estimate eight regressions: one each for the gross and net performances of the average individual investors for four types of accounts.

Third, we consider two more factors, other than the market one, by following the three-factor model derived by Fama and French (1993). For example, to evaluate the performance of average individuals, we estimate the following monthly time-series regression:

$$\left(RI_t^{gr} - R_{ft}\right) = \alpha_j + \beta_j\left(R_{mt} - R_{ft}\right) + s_j SMB_t + h_j HML_t + \epsilon_{it},$$

where SMB_t is the return on a value-weighted portfolio of small stocks minus the return on a value-weighted portfolio of large stocks, and HML_t is the return on a value-weighted portfolio of high book-to-market stocks minus the return on a value-weighted portfolio of low book-to-market stocks. Again, we estimate eight regressions based on the gross and net performances for four types of accounts.

B. Results

The results of the risk-adjusted return analysis are presented in Table 4 Panels A, B, C, and D present the results for the gross and net performances for the accounts of the small, middle, big, and super investors. Each panel is divided into two sides, the left side is for the gross return analysis, and the right side is for the net return analysis.

For small investors, neither the market-adjusted return, nor the intercept test from the CAPM model, nor the intercept test from Fama and French's (1993) three-factor model is reliably different form zero. After considering the transaction costs, the net excess return from all three performance measures for the small investors are all significantly below zero. The middle investors earn positive gross excess returns, but negative net excess returns. The big investors also earn positive gross excess returns, and their net excess returns are not reliably different from zero.

Table 4 shows that the average monthly excess gross (net) return for super investors is about 10% (8%) according to both the CAPM model and Fama and French's (1993) three-factor model. Cross-sectionally, the super investors outperform the other three groups of investors by more than 5% in both gross and net excess returns.

Also noteworthy in these results are the coefficient estimates on the market, size, and the book-to-market factors. The market betas for stocks held by all four groups of individual investors are greater than one. We don't find significant loadings on the *HML* factor for most of the accounts. The individual investors in the Chinese stock market might have difficulties in telling the differences between value and growth stocks. They naively assume that stocks with lower prices are value stocks, without considering the underlying book value of the companies. We also observe that small, middle, and big investors are allured by small stocks, which is indicated by the significant loadings on the *SMB* factor.

For small, middle, and big investors, both the CAPM and Fama and French's (1993) three-factor model report a high adjusted R-square value around 90%. But these models are poor in explaining the returns of super investors, with an adjusted R-square value around 40%. This difference might indicate that the super investors select stocks distinctly different from the other investors. The wealth level seemingly makes a difference in the stock picking abilities because super investors earn much higher excess returns.

TABLE 4 SUMMARY OF THE PERCENTAGE MONTHLY ABNORMAL RETURN MEASURES

Notes: Gross returns are based on daily position statements for 1.8 million individual investors at a national brokerage firm from January 2007 to October 2009. Net returns are gross returns adjusted by trading costs. Panel A-D presents results for the gross (net) return on a portfolio that mimics the average investors of different accounts. Market-adjusted return is the return on the investor portfolio less the return on index. CAPM is the results from a time-series regression of the investor excess return on the market excess return. Fama-French three-factor is the results from time-series regression of investor excess return on the market excess return, a book-to-market portfolio, and a size portfolio. *P*-values are presented in parentheses. *** Significant at the 1% level. ** Significant at the 5% level.* Significant at the 10% level.

	Gross Percentage Monthly Returns					Net Percentage Monthly Returns				
	Excess	Coefficient Estimate on:			Adjusted	Excess	Coefficient Estimate on:			Adjusted
	Return	$(R_{mt}-R_{ft})$	HML_t	SMB_t	R^2	Return	$(R_{mt}-R_{ft})$	HML_t	SMB_t	R^2
Panel A: Small Investors (≤ RMB 100K)										
Market-adjusted return	0.031*					-0.037***				
	(0.100)					(0.000)				
CAPM	0.017	1.042***			83.0	-0.027***	0.942***			83.6
	(0.129)	(0.000)				(0.000)	(0.000)			
Fama-French three-factor	0.001	0.999***	0.240**	0.746***	95.2	-0.034***	0.883***	0.350	0.490***	85.9
	(0.781)	(0.000)	(0.035)	(0.000)		(0.000)	(0.000)	(0.160)	(0.000)	
Panel B: Middle Investors (RMB 100K ~ RMB 1M)										
Market-adjusted return	0.046**					-0.018***				
	(0.021)					(0.000)				
CAPM	0.030***	1.145***			82.4	-0.011**	0.982***			88.3
	(0.005)	(0.000)				(0.039)	(0.000)			
Fama-French three-factor	0.018**	1.118***	0.125	0.569***	87.3	-0.016***	0.934***	0.297	0.396***	82.5
	(0.042)	(0.000)	(0.356)	(0.000)		(0.000)	(0.000)	(0.103)	(0.000)	
Panel C: Big Investors (RMB 1M ~ RMB 5M)										
Market-adjusted return	0.056***					0.038***				
	(0.005)					(0.013)				
CAPM	0.040***	1.122***			85.4	0.009*	1.020***			80.8
	(0.001)	(0.000)				(0.076)	(0.000)			
Fama-French three-factor	0.028***	1.095***	0.117	0.609***	91.8	0.005	0.983***	0.247**	0.260**	91.0
	(0.001)	(0.000)	(0.436)	(0.000)		(0.314)	(0.000)	(0.029)	(0.021)	
Panel D: Super Investors (≥ RMB 5M)										
Market-adjusted return	0.128***					0.097***				
	(0.002)					(0.006)				
CAPM	0.105***	1.436***			42.9	0.079***	1.213***			41.3
	(0.003)	(0.000)				(0.004)	(0.000)			
Fama-French three-factor	0.097**	1.430***	-0.048	0.401	39.9	0.075**	1.200***	0.089	0.196	37.6
	(0.011)	(0.000)	(0.919)	(0.453)		(0.021)	(0.000)	(0.823)	(0.678)	

C. Turnover and Return

Barber and Odean (2000) find a negative relation between the performance and the trading frequency of individual investors. We now turn our focus on the trading frequency of super investors. To do so, we form quintile portfolios based on the monthly turnover for each group of individual investors. We define the monthly turnover as the sum of turnovers for buy and sell transactions. We then calculate the average gross and net returns for each quintile portfolio.

Panels A, B, C, and D in Table 5 present the gross and net returns for each quintile for the small, middle, big, and super investors respectively. Focusing first on the gross performance (topline of each panel), we find that the high turnover portfolios earn higher average returns than the low turnover portfolios for all four groups of investors, and the difference is significantly different from zero. Moreover, the relation between the turnover and the gross returns is positively monotonic: the more individual investors trade, the higher the gross returns are.

After considering transaction costs, we find that the small, middle, and big investors all earn negative net returns. The only exception is the super investors. These investors manage to earn positive net returns. Moreover, small and middle investors suffer from excessive trading. Their net returns decrease with the increase in their trading frequency. On the other hand, we find that big and super investors continue to exhibit the positive relation between net returns and turnover.

In sum, Table 5 shows that more trading increases the gross returns of small, middle, big and super investors, but the increases are not sufficient to compensate for the increases in the trading costs for small and middle investors. We also present the full sample results in Panel E of Table 5. The pattern is very similar to Barber and Odean (2000) in that turnover benefits the gross returns but hurts the net returns. In the far left column of Table 5, we present the gross and net returns for all four groups of investors without partitioning them into turnover quintiles. We find that the gross and net returns increase with the value of the individual investors' portfolios.

TABLE 5 GROSS/NET RETURNS FOR INVESTOR QUINTILES FORMED ON MONTHLY AVERAGE TURNOVER

Gross returns are based on daily position statements for 1.8 million individual investors at a national brokerage firm from January 2007 to October 2009. Net returns are gross returns adjusted by trading costs. For each group of investors, we divide investors into quintiles by monthly turnover. Panel A-B shows net return decreases with the increase of turnover for less wealthy investors. Panel C-D shows net return increases with the increase of turnover for more wealthy investors. Panel E repeat the exercise pooling all levels of wealth l and shows turnover hurts net returns on average. Difference between highest turnover quintile and lowest turnover quintile is included. *P*-values are presented in parentheses.

	All	Turnover Quintile					
		1 (Low)	2	3	4	5 (High)	Difference: High-Low
				Panel A: Small Investors (≤ RMB100K)			
Gross Return	0.49	0.25	0.31	0.35	0.46	1.20	0.95*** (0.001)
Net Return	-7.99	-7.61	-7.72	-7.93	-8.11	-8.22	-0.61*** (0.000)
				Panel B: Middle Investors (RMB100K ~ RMB1M)			
Gross Return	0.67	0.41	0.46	0.49	0.56	1.86	1.45* (0.085)
Net Return	-7.41	-7.16	-7.27	-7.45	-7.63	-7.48	-0.32 (0.290)
				Panel C: Big Investors (RMB1M ~ RMB5M)			
Gross Return	0.79	0.56	0.64	0.73	0.83	1.45	0.886*** (0.000)
Net Return	-0.82	-0.90	-0.88	-0.87	-0.84	-0.45	0.458*** (0.000)
				Panel D: Super Investors (≥ RMB5M)			
Gross Return	1.65	0.69	0.94	1.12	1.16	6.04	5.355** (0.037)
Net Return	1.28	0.48	0.70	0.85	0.88	4.99	4.509** (0.049)
				Panel E: All Investors			
Gross Return		0.35	0.40	0.44	0.54	1.56	1.212** (0.021)
Net Return		-6.96	-7.21	-7.40	-7.54	-7.31	-0.350* (0.083)

We test the robustness of our results across different position sizes and turnovers by forming 5 by 5 portfolios based independently on these factors. In the previous test, the cutoffs at position size were pre-determined as 100K, 1M, 5M, and above 5M. We present the net returns of double-sorted portfolios in Table 6. The results show that the bigger portfolios outperform smaller portfolios across all levels of turnover. Moreover, high turnover erodes the net returns of the less rich investors' portfolio. For more wealthy investors, the net returns earned from more trading are not reliably different from the net returns earned from less trading. This observation is consistent with our previous findings that excessive trading hurts less wealthy individual investors the most. The super investors manage to compensate for the increased transaction costs from trading more.

TABLE 6 NET RETURNS FOR INVESTOR QUINTILES FORMED ON MONTHLY AVERAGE TURNOVER AND PORTFOLIO SIZE

Investors are independently sorted into turnover quintiles and size quintiles respectively. Portfolio size is a proxy for investors' wealth level. Net returns are gross returns adjusted by trading costs. For all turnover level, net returns increases with wealth increases. For lower wealth level, net returns decreases with turnover increase. However such relationship becomes insignificant for higher wealth level.

	Monthly Turnover Quintile					
Portfolio Size Quintile	1 (Low)	2	3	4	5 (High)	Difference: High-Low
1 (Small)	-7.13	-7.25	-7.62	-7.94	-7.87	-0.735***
2	-7.58	-7.63	-7.85	-8.02	-8.07	-0.484***
3	-7.65	-7.69	-7.83	-7.92	-7.68	-0.033
4	-7.44	-7.52	-7.62	-7.73	-7.60	-0.156
5 (Large)	-5.53	-5.83	-5.90	-5.90	-5.51	0.019
Difference: Large-Small	1.601***	1.416***	1.720***	2.042***	2.355***	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

*** Significant at the 1% level. ** Significant at the 5% level.* Significant at the 10% level.

III. Information and Performance

A. Hypothesis Development

Barber and Odean (2000) show that overconfidence is the reason why individual investors trade excessively. Meanwhile, the increases in transaction costs decrease the net returns earned by individual investors. We identify super investors earning a positive excess return by trading a lot in section II of our paper. So, what is the source of their superior performance? Could it be skill, an informational advantage, or both?

To answer this question, we perform an event study to capture the trading behaviors and returns around certain events in the Chinese stock market.[5] Because shorting in the Chinese stock market is not allowed, we limit our events to good news reaching the market: for example, a high stock dividend announcement.

The listed companies in the Chinese stock market are reluctant to pay cash dividends. Instead, they prefer to distribute stock dividends. We define a high stock dividend as when a company declares at least a 50% dividend. There are about 59 high stock dividend events during our sample period. On average, the stock prices rise about 5.8% (*t-stat* =6.4) in the 15 days after the dividends are paid.

Paying stock dividends doesn't change companies' fundamentals at all. However, stock prices always rise after managements make such decisions. So, why does the market react positively towards such a policy? Behavioral theory believes that the distribution of stock

[5] Geng and Lu (2012) study stocks selections of super individual investors when they do not have inside information. They find super individual investors prefer stocks with low institutional holdings and with recent losses, because these stocks are more vulnerable to manipulations.

dividends makes stocks appear to be cheaper and creates the illusion of a nominal price. A high stock dividend (50% dividend ratio) can reduce the stock price by at least 30%. As documented in the case of a stock split by Baker and Wurgler (2004), the nominal-price illusion could stimulate a positive reaction from investors and cause a price bubble.[6] It turns out that stock dividends play the same role as a stock split in fooling naïve individual investors.

As such, we conjecture that the average individual investor is allured by the reduced prices and buys stocks after the announcements. Meanwhile, the super investors with private information of the forthcoming high dividend announcement can take advantage of the less wealthy individual investors' reaction by purchasing stocks before announcements and selling them afterwards. If we use the buy-sell imbalance to indicate the trading direction of individual investors, then we can expect that super investors are net buyers (sellers) of stocks that pay high dividends before (after) the announcements. Meanwhile, less wealthy individual investors are net sellers of stocks that pay high dividends before (after) the announcements.

The assumption that all super investors are informed about all of the high dividend announcements ahead of time is unreasonable. A natural guess is that super investors are locally informed. In other words, we conjecture that the local super investors buy stocks with high dividends before the announcements and sell them afterwards and that non-local super investors do not react in this way.

[6] A stock dividend and a stock split are different in corporate decision-making, accounting treatment, signal sending to the market etc. However, they both could make stocks appear to be cheaper. For instance, both a 1:2 stock split and a 100% stock dividend cut the price in half.

Based on the above analysis, we make the following hypotheses:

Hypothesis1: Local super investors are net buyers before high stock dividend announcements; they are net sellers after the announcements.

Hypothesis2: Local super investors gain by trading on the information about forthcoming high dividend announcements.

B. Methods and Variable Definition

Following Barber and Odean (2008), we use buy-sell imbalances to indicate the trading directions of the individual investors. The buy-sell imbalance is calculated as:

$$BSI_{i,t} = \frac{\Sigma_{h=1}^{n} Buy_{i,t} - \Sigma_{h=1}^{n} Sell_{i,t}}{\Sigma_{h=1}^{n} Buy_{i,t} + \Sigma_{h=1}^{n} Sell_{i,t}}$$

where *n* is the number of investors in each group that trades high dividend stock *i* in day *t*, and the *Buy* (*Sell)* is the volume of each transaction. As a robustness check, we also repeat the buy-sell imbalance with the value of each transaction in our analysis. To capture the impact of the high dividend announcement, we calculate the abnormal buy-sell imbalance by subtracting the benchmark level of the buy-sell imbalance from the actual buy-sell imbalance. The benchmark is estimated as the average buy-sell imbalance 360 days prior to the dividend-announcement event windows.[7]

[7] We test with a different windows size, i.e. 180 days, the results are similar.

To identify the local and non-local individual investors, we obtain the registered cities of the listed companies and the branch address of the anonymous broker. If the distance between registered city and broker branch is less than 300 kilometers, we label investors as local investors. Otherwise, they are non-local investors. For each incidence of events, local and non-local investors might vary.

We also calculate the realized gain/loss and the unrealized gain/loss in the event periods. If investors did not sell the stock at the end of event window, we assume they sell it at the next day's closing price and regard this portion of the gain/loss as unrealized.

C. Empirical Results

The buy-sell imbalances for each group of individual investors before and after the announcements are presented in Table 7. Panels A and B present the buy-sell imbalance as the number of shares traded for local and non-local individual investors respectively.

The results in Table 7 confirm hypothesis 1 on the trading direction of individual investors. On average, local super investors buy before the announcements and sell afterwards. The buy-sell imbalances of non-local small, middle, and big investors are not significantly different from zero. They do not seem to trade much of the high dividend stocks or at least they are in disagreement about whether to buy or sell such stocks. The difference in trading between small investors and super investors is significantly different from zero. We believe this significance is because local super investors are better informed than their counterparts about the forthcoming high dividend announcements. Super investors take advantage of such information by buying ahead of the news.

As for non-local super investors, they are neutral about high dividend stocks. If they are not aware of the coming news and do not buy before the announcements, they probably are sophisticated enough not to buy after the announcements.

The non-local small and middle investors are net sellers (buyers) of high dividends stocks before (after) the announcements. And it seems they react to such news more strongly after it becomes public. For big investors, their trading before the announcements is even, but they also buy high dividend stocks after the announcements.

We repeat the exercise with the value of shares traded for local and non-local individual investors and present the results in Panels C and D. The results are similar.

TABLE 7 BUY/SELL IMBALANCE AROUND THE HIGH STOCK DIVIDEND ANNOUNCEMENT (30 DAYS)

Local investors are those in the 300 km around cities where listed firms registered. Net Buy is the difference between buy and sell divided by the sum of buy and sell. Before and After are periods before and after high stock dividend announcements. Difference between small accounts and super accounts are reported as well. *P*-values are presented in parentheses.

	Account Size				Difference
	Small	Middle	Big	Super	Super-Small
			Panel A: Local Investors Net Buy Volume		
Before	0.016	0.012	0.045	0.357***	-0.341***
	(0.734)	(0.804)	(0.554)	(0.009)	(0.005)
After	0.030	0.091**	0.016	-0.224*	0.254**
	(0.367)	(0.022)	(0.826)	(0.078)	(0.024)
			Panel B: Non-local Investors Net Buy Volume		
Before	-0.044**	-0.036**	0.001	-0.003	-0.040
	(0.016)	(0.035)	(0.982)	(0.953)	(0.501)
After	0.086***	0.090***	0.081***	-0.002	0.087
	(0.000)	(0.000)	(0.006)	(0.977)	(0.133)
			Panel C: Local Investors Net Buy Value		
Before	0.011	0.015	0.048	0.359***	-0.348***
	(0.821)	(0.752)	(0.531)	(0.008)	(0.004)
After	0.037	0.090**	0.011	-0.221*	0.257**
	(0.287)	(0.026)	(0.881)	(0.084)	(0.023)
			Panel D: Non-local Investors Net Buy Value		
Before	-0.045**	-0.038**	-0.001	-0.013	-0.033
	(0.012)	(0.032)	(0.979)	(0.827)	(0.584)
After	0.083***	0.091***	0.079***	-0.004	0.087
	(0.000)	(0.000)	(0.008)	(0.940)	(0.137)

*** Significant at the 1% level. ** Significant at the 5% level.* Significant at the 10% level.

The advantage from trading on inside information is supposed to be profitable. Panels A and B in Table 8 present the realized and unrealized returns from the trading of high dividend stocks by local individual investors. The realized gains are calculated as the difference between selling prices and average costs divided by average costs. The unrealized gains are calculated as the difference between closing prices and average costs divided by average costs. Our data set provides the average costs of the shares held by each investor on a daily basis.

TABLE 8 REALIZED AND UNREALIZED RETURN AROUND THE HIGH STOCK DIVIDEND ANNOUNCEMENT (30 DAYS)

Local investors are those in the 300 km around cities where listed firms registered. Realized return is calculated if investors sell their holdings. Unrealized return is calculated using the closing price at the end of 30 days if investors still hold their positions. Before and After are periods before and after high stock dividend announcements. Difference between small accounts and super accounts are reported as well. *P*-values are presented in parentheses.

	Account Size				Difference
	Small	Middle	Big	Super	Super-Small
Panel A: Local Investors Realized Return					
Before	0.017***	0.017***	0.041***	0.036**	0.019
	(0.000)	(0.000)	(0.000)	(0.033)	(0.310)
After	0.007***	0.006***	0.048***	0.058**	0.030**
	(0.000)	(0.000)	(0.000)	(0.015)	(0.034)
Panel B: Local Investors Unrealized Return					
Before	-0.015***	-0.021***	-0.002	0.001	0.015
	(0.000)	(0.000)	(0.850)	(0.981)	(0.411)
After	-0.006**	-0.010***	-0.003	0.003	0.008
	(0.028)	(0.000)	(0.748)	(0.953)	(0.665)
Panel C: Non-local Investors Realized Return					
Before	0.014***	0.006***	0.007***	0.004	0.019***
	(0.000)	(0.000)	(0.000)	(0.334)	(0.000)
After	0.003***	0.011***	0.018***	0.013***	0.010**
	(0.004)	(0.000)	(0.000)	(0.005)	(0.030)
Panel D: Non-local Investors Unrealized Return					
Before	-0.023***	-0.018***	-0.004	-0.009	0.014**
	(0.000)	(0.000)	(0.204)	(0.335)	(0.032)
After	-0.015***	-0.013***	-0.005**	-0.011	0.004
	(0.000)	(0.000)	(0.037)	(0.232)	(0.496)

*** Significant at the 1% level. ** Significant at the 5% level.* Significant at the 10% level.

Because of the disposition effect, individual investors tend to sell winning stocks but hold on to losing stocks. Not surprisingly, we find that those local individual investors who sell high dividend stocks realize positive returns, while super investors earn the highest returns of all of the groups of investors. Indeed, their realized returns are 3.6% before the announcements and 5.8% after the announcements. For local small and middle investors, the positive realized returns are offset by the negative unrealized returns. Considering less wealthy individual investors are net buyers after the announcements, we believe less wealthy individual investors buy overpriced stocks and hold them with losses.

Panels C and D in Table 8 present the realized returns and unrealized returns for the trading of high dividend stocks by non-local individual investors. We find that non-local super investors do not earn significant returns during the events. It is reasonable that if they do not buy high dividend stocks before the announcements, then they were not aware of the news. They are also sophisticated enough to avoid overpriced stocks after the announcements. This is consistent with our findings from the analysis of the buy-sell imbalance that non-local super investors are neither net buyers nor net sellers of high dividend stocks. For less wealthy individual investors, their realized and unrealized returns offset each other as well.

D. Robustness Check

We observe that not all companies that do well in the previous fiscal year distribute stock dividends or pay any kind of dividends. Also companies with good operational results do not always attract investors' attention. We assume that super investors trade on their private information about forthcoming stock dividends announcements. Thus, we expect that they do not prefer companies with good fundamentals but companies that issue stock dividends.

Under this conjecture, we look for a group of companies that have similar fundamentals, compared to those paying high stock dividends, but that do not issue stock dividends at all. Following the literature, we consider the Earnings per Share (EPS), total asset (log), asset growth, profitability, and the book-to market ratio in selecting the control companies. Using the Propensity Score Match (PSM), we are able to find one-to-one matches between the high stock dividend companies and control companies. We repeat the buy-sell imbalance analysis on the matched companies around the dates of the dividend announcements.

TABLE 9 BUY/SELL IMBALANCE AROUND THE HIGH STOCK DIVIDEND ANNOUNCEMENT (CONTROL FIRM, 30 DAYS)

Control firms are identified using Propensity Score Match. Local investors are those in the 300 km around cities where listed firms registered. Net Buy is the difference between buy and sell divided by the sum of buy and sell. Before and After are periods before and after high stock dividend announcements. Difference between small accounts and super accounts are reported as well. *P*-values are presented in parentheses.

	Account Size				Difference
	Small	Middle	Big	Super	Super-Small
	Panel A: Local Investors Net Buy Volume				
Before	0.010	0.045	0.052	0.096	0.086
	(0.816)	(0.284)	(0.485)	(0.353)	(0.381)
After	0.072	-0.014	-0.065	-0.067	-0.139
	(0.115)	(0.727)	(0.303)	(0.464)	(0.131)
	Panel B: Non-local Investors Net Buy Volume				
Before	0.016	-0.007	-0.041	0.025	0.008
	(0.349)	(0.576)	(0.102)	(0.718)	(0.900)
After	0.033**	0.016	0.021	-0.044	-0.078
	(0.019)	(0.261)	(0.429)	(0.506)	(0.235)
	Panel C: Local Investors Net Buy Value				
Before	0.010	0.042	0.050	0.098	0.087
	(0.810)	(0.314)	(0.504)	(0.341)	(0.370)
After	0.069	-0.016	-0.069	-0.064	-0.133
	(0.130)	(0.693)	(0.276)	(0.482)	(0.148)
	Panel D: Non-local Investors Net Buy Value				
Before	0.014	-0.008	-0.042*	0.030	0.016
	(0.413)	(0.553)	(0.100)	(0.654)	(0.814)
After	0.030**	0.015	0.019	-0.047	-0.077
	(0.035)	(0.267)	(0.488)	(0.484)	(0.239)

*** Significant at the 1% level. ** Significant at the 5% level.* Significant at the 10% level.

Panels A and B in Table 9 present the results of the buy-sell imbalance analysis. In general, neither the local nor the non-local individual investors in the medium, big, and super groups exhibit significant demands for the stocks of control companies during the event windows. This finding is consistent with our conjecture that local super investors trade on their information about forthcoming good news.

We repeat the exercise with the value of shares traded for local and non-local individual investors and present the results in Panels C and D in Table 9. The results are similar.

IV. Conclusion

We analyze the returns earned on common stock investments by 1.8 million individual investors in a leading brokerage firm in the Chinese stock market for three years ending in October 2009. We find that overall the individual investors underperform the market after considering the trading cost. However, a certain group of super investors earn a positive excess return on top of the trading cost. Moreover, the more they trade, the higher the net return that they earn. This finding contradicts Barber and Odean's (2000) finding that excessive trading hurts individual investors' wealth. We confirm their results with a subsample of less wealthy individual investors.

After studying the buy-sell imbalances and the realized/unrealized gains of individual investors around dividend announcements, we find that super investors buy high dividend stocks before the announcements and sell them when the information becomes public. They earn a 10% return from trading these stocks. We believe that an informational advantage helps super individual investors to achieve their positive alpha.

CHAPTER 2

IMPLICITLY-COORDINATED MANIPULATION:

A SCHEME IN THE CHINESE STOCK MARKET[8]

Listed stocks on the Chinese equity market sometimes experience significant abnormal returns and trading volume after publicly announced and remotely related positive news. The increase in price is hardly justified by the increase in the fundamental value conveyed by the news event. One recent event of this type affected the so-called “Nobel Prize Concept” stocks. Nobel Prizes in Physics, Chemistry, and in Physiology or Medicine are awarded to prominent scientists for their advanced contributions. Technologies recognized by Nobel Prizes are proved valid and useful long before the announcements. However, each announcement in the above category leads to sudden and extreme increases in the prices and trading volumes of some of the listed companies on the Chinese stock market. Table 10 provides an incomplete list of “Nobel Prize Concept” stocks that experienced abnormal returns and volumes after the prize announcements of 2012.[9]

TABLE 10 AN INCOMPLETE LIST OF NOBEL PRIZE CONCEPT STOCKS IN 2012

This table provides an incomplete list of “Nobel Prize Concept” stocks that experienced abnormal returns and volumes after the prize announcements of 2012.

Date	Prize	Contributions in	Affected Stocks
2012.10.8	Physiology or Medicine	Stem Cell	VcanBio (600645) 16% increase for 2012.10.9-10.10
2012.10.9	Physics	Quantum Systems	HansLaser (002008) 10% increase on 2012.10.10
2012.10.10	Chemistry	G-protein-coupled receptors	ChangchunHiTech (000661) 10% increase on 2012.10.11

[8] This chapter is based on a joint work with Xiaomeng Lu.

[9] The 10% increase is the daily upper price limit for listed stocks on the Shanghai and Shenzhen Stock Exchanges.

Each of these firms had business that was remotely related to the contribution of the Nobel Prizes. The consensus among professional practitioners is that the announcement of Nobel Prizes should have little impact on the valuation of these firms.

But not all firms related to the Nobel Prize contribution experience a similar increase in their price and trading volume. For example, after the announcement of the Nobel Prize in Physiology or Medicine, VcanBio that specializes in stem cell research increased 6% on the first trading day, followed by a 10% return on the subsequent day. Yet, Shanghai Fosun Pharmaceutical, also specializing in stem cell research and also categorized as a "Nobel Prize Concept" stock by the financial media, did not experience any abnormal return or volume during the same period. Its return was only 1.7% and -0.4% on the two days after the announcement respectively, and the trading volume was comparable to the volume before the announcement. Therefore, the phenomenon in the case of VcanBio differs from the phenomenon that occurs when a stock price reacts to attention-grabbing news, as documented in the literature. Another typical case of this phenomenon, the case of Zhejiang Dongri, is discussed in the Appendix A. Events of this type occur frequently in the Chinese stock market, but are rarely seen in advanced financial markets. One potential explanation for this phenomenon is market manipulation. Anecdotal evidence suggests that a large number of speculative manipulators exist who are creating the events.

Although the events look like normal pump-and-dump events, evidence suggests that this phenomenon differs from manipulations documented in the literature in two ways. First, there is no written or oral agreement among the manipulators. After observing a publicly announced news event, some of them express their positive views about certain stocks in internet chat rooms or other informal but legal venues. If many of them share the same optimistic view and they estimate that sufficient capital exists to pull it off, then they start the “attack”. Second, manipulation is not limited to a fixed set of investors. Their coordination is random and participation is wide spread. Every incident could have a different composition of participants.

Several key features of the Chinese stock market are essential for such manipulation to be profitable. First, individual investors dominate the Chinese stock market, and they tend to exhibit behavioral biases in their trading decision. Second, shorting stocks has not been allowed until March of 2010 in China. After that, shorting has been limited to certain stocks and its cost has become extremely high (close to 10% annually). When overpricing occurs in the market, arbitrageurs cannot correct the mispricing by short selling. Another force that can correct mispricing is for firms to issue more shares when their shares are overvalued. Frazzini and Lamont (2008) provide empirical evidence that firms issue shares in response to overpricing because of high investor sentiment in the US stock market. However, this mechanism is also impaired in the Chinese equity market. Secondary issuance of stock is under strict regulation. Issuance of additional shares usually takes months for a listed firm. Therefore, when overpricing occurs for a certain firm, the firm cannot take advantage of the mispricing by issuing shares instantly.

The phenomenon we study is related to several trading patterns of individual investors documented in the literature. Odean (1998) finds the disposition effect, that is, investors tend to sell winners too soon and hold on to losers for too long. The empirical literature also provides various evidence of individual trading behavior at attention-grabbing events. Barber and Odean (2008) conduct a comprehensive study on individual trading behavior in the United States. They find that individual investors purchase a stock when the stock experiences an extreme one-day return, abnormal trading volume, or an attention-grabbing news event. Seasholes and Wu (2007) confirm this trading pattern with Chinese market data. They also find that smart traders accumulate shares during upper price-limit events by buying from individuals who are willing to sell for a gain. The smart traders then sell the following day to another group of individuals who are eager to buy.

Given these well-documented behavioral biases and limits of arbitrage, the natural question to ask is whether smart investors can manipulate the price to benefit themselves. Further, what types of stocks are more vulnerable to this type of manipulation? What is the implication on the market's efficiency? These questions are important both to researchers and regulators. While manipulative activities seem to have declined on the main exchanges in developed markets, they are still a serious issue in emerging financial markets. Regulators are always concerned about "pump-and-dump" schemes, because small retail investors are usually the victims of these manipulations.

Allen and Gale (1992) define trade-based manipulation as the instance that a trader can profit from simply buying and selling a stock without taking any action that alters the value of a firm. Jiang et al. (2005) finds no abnormal return in the long run after manipulation by stock pools. Assuming that all traders are rational, Allen and Gale (1992) and Aggarwal and Wu (2006) show that trade-based manipulation can still be profitable if the typical traders cannot distinguish manipulators from informed traders. Yet, Aggarwal and Wu (2006) find a negative return after the manipulation cases in SEC litigation releases. Our model differs from this strand of literature in that, no one in the market needs to have superior information about the firms. If investors are not fully rational, the possibility exists for manipulators to take advantage of the other investors' behavioral biases to make money even if no one is expected to have private information about the firm. We find a new type of market manipulation that is difficult to eliminate. The manipulators we study in this paper do not necessarily release false rumors about the firm's fundamentals, which is potentially illegal and subject to surveillance. Moreover, they do not rely on frequent buying and selling between their accounts to drive up the price, which is the major type of manipulation under surveillance. Therefore, strengthening surveillance on informed trading is also unlikely to eliminate this type of manipulation. We find a strong negative price impact on stock returns after this new type of manipulation. In this sense, we provide a case in which smart money creates market inefficiencies, instead of eliminating them. Furthermore, we use a unique data set from a brokerage firm that provides evidence that is consistent with the trading pattern of the manipulator and the profitability of manipulation. Super individual accounts (accounts with asset value over five million RMB), which we suspect to be held by the manipulators, accumulate stocks to pump up the stock price during on the first day of manipulation and dump them on the subsequent trading day. To the contrary, small individual investors are the net seller during the pump period and the net buyer during the dump period. Moreover, super individual accounts have much higher portfolio turnover and returns during the manipulation period.

Mei et al. (2004) build an equilibrium model to demonstrate how “smart money” can profit from irrational investors who suffer from loss aversion. However, they envision a single manipulator behind the manipulation. A crucial difference in our model from theirs is that public news events that are remotely related to certain firms serve as a coordination device among a large number of manipulators. This unique feature directly explains the puzzle of significant increases in a stock price and its trading volume after a news event that is not related to any concrete changes in the firm’s fundamentals, which is similar in spirit to the currency attack model by Morris and Shin (1998).

The rest of the paper is organized as follows. In the next section, we present our model of implicitly coordinated stock-price manipulation and derive testable hypotheses from the model. In section II, we describe the data used in this study. Section III describes the empirical methodology and documents the two key predictions of our model: (a) stocks with low institutional holdings and previous declines in value are more vulnerable to attack from speculative manipulators, and (b) the target stocks of speculative manipulators underperform after the event. Section IV focuses on the trading records of speculative manipulators and behavioral investors and provides additional evidence of the existence of such a strategy. Section V concludes.

I. The model

A. Assumptions

Following the basic setup of DeLong, Shleifer, Summers and Waldmann (DSSW) (1990), we consider a model of four periods—0, 1, 2, and 3— and two assets: cash and a single stock. Cash pays no net return. Stock is in Φ of net supply and pays a certain dividend of V at period 3. We assume there is no short sale of the stock, no leverage on the stock, and no secondary issuance by the firm.

The model comprises four types of investors, two of which suffer from different types of behavioral biases. Type 1 investors are positive feedback investors that are individual investors endowed with cash that suffer from a positive feedback trading bias, present in a measure of one. Type 2 investors are loss aversion investors that are individual investors who hold the stock initially. They sell the stock if and only if the price is higher than its purchase cost. Type 3 investors are fundamental investors whose demand of a stock depends only on the price relative to its fundamental value, that is, the expected value of the dividend. Type 4 is a large number of speculative manipulators who are each endowed with cash in amount c and who maximize their utility as a function of period 3 consumption. We assume that all investors are risk neutral.

The structure of the model is described as follows:

Period 0

The public expectation of the dividend payoff of the stock is V, and the stock price at period 0 is V. At period 0, the stock has a total of float shares Φ of which θ fraction is held by loss aversion investors, and $1 - \theta$ fraction is held by fundamental investors. All remaining shareholders are loss aversion investors who have suffered losses, and their purchase costs have a distribution function $m(P)$. Loss aversion investors sell the stock if and only if the price is higher than its purchase cost.

A public news signal is disclosed in period 0. The signal implies that the dividend at period 3 is $V + \varepsilon$ where ε is positive but infinitesimal. The signal generates varying degrees of attention: n represents how many speculative manipulators observe the signal, and n is common knowledge among the speculators.

Period 1

After observing the public signal and n, each manipulator chooses his or her strategy. The equilibrium of the model depends on the realization of n.

For any $P_1 > V$, the fundamental investors' supply of the stock is $\Phi(1 - \theta)$, and the loss aversion investors' supply of the stock is $m(P_1)\Phi\theta$.

If the event does not attract enough attention from the speculative manipulators, that is, $nc \leq \Phi(1 - \theta)V$, then the manipulators not moving is an equilibrium. In this case, $P_0 = P_1 = P_2 = P_3 = V$, and the trading volume for each period is zero.

If $nc > \Phi(1 - \theta)V$, then each speculator spending c to buy the stock is an equilibrium for a certain range of parameter values. In this case, P_1 is determined by $nc = \Phi[(1 - \theta) + \theta m(P_1)]P_1$ where $m(P_1)$ is the fraction of the individually held shares whose purchase costs are below P_1, and the trading volume in terms of the stock value is nc in period 1.

Period 2

Following DSSW (1990), we assume that the demand of the positive feedback investors in period 2 responds to the price change between periods 0 and 1 and is invariant to the price at period 2. That is, positive feedback investors place market orders after observing prices in previous periods, and before the price realization in the current period. We assume the total demand from all of the positive feedback investors in period 2 is $\beta(P_1 - P_0)$ where β is the positive feedback coefficient. The trading volume in terms of the stock value at period 2 is $\beta(P_1 - P_0)P_2$.

Period 3

In period 3, the realization of the dividend is $V + \varepsilon$. There is no trading of stock, and investors who hold the stock at period 3 are paid the publicly known dividend $V + \varepsilon$. Since the dividend is known for certain in period 3, the price of the stock is pinned to the fundamental value of $V + \varepsilon$.

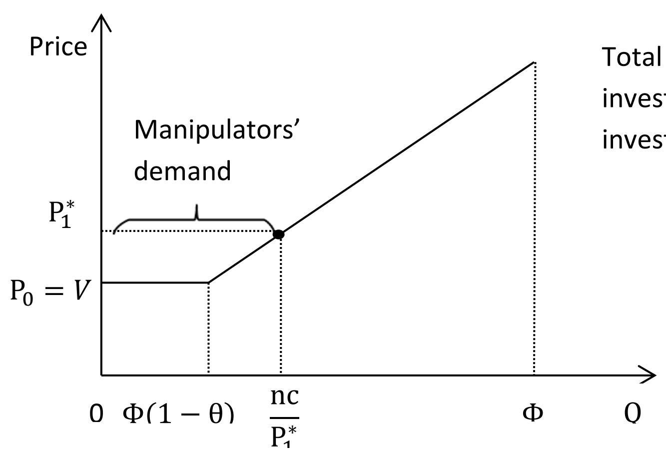

FIGURE 2.A SUPPLY AND DEMAND OF SHARES FOR EACH INVESTOR TYPE

This figure shows the supply and demand of shares by each investor type at equilibrium when $nc > \Phi(1-\theta)V$. The upper figure represents the supply and demand in period 1, and the lower figure depicts the supply and demand in period 2.

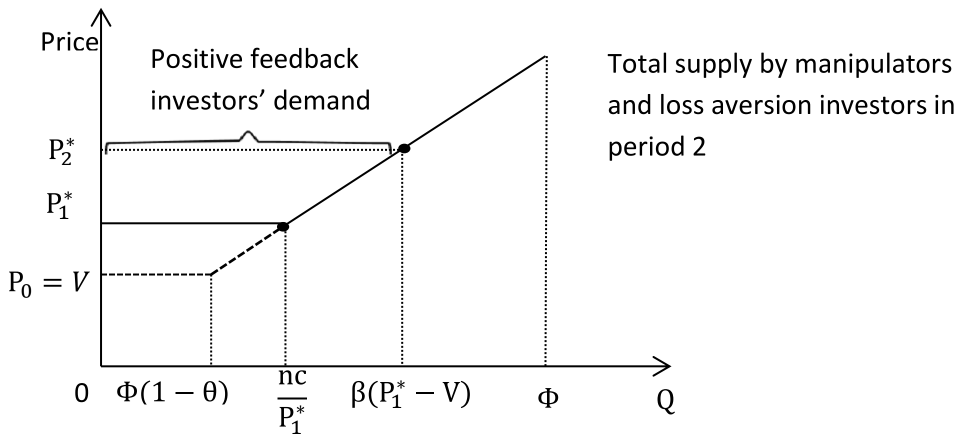

FIGURE 2.A (CONTINUED) SUPPLY AND DEMAND OF SHARES FOR EACH INVESTOR TYPE

This figure shows the supply and demand of shares by each investor type at equilibrium when $nc > \Phi(1-\theta)V$. The upper figure represents the supply and demand in period 1, and the lower figure depicts the supply and demand in period 2.

B. Solution of the Model

We focus on the equilibrium when $nc > \Phi(1-\theta)V$ and derive the condition for the existence of this equilibrium. As long as the demand for positive feedback trading is sufficiently high, P_2 is greater than P_1, the demand ensures that all of the speculators sell out at period 2 with profit. At the same time, loss aversion investors whose purchase costs lie between P_1 and P_2 also sell out at time 2. The P_2 is determined by the following condition:

$$[m(P_2) - m(P_1)]\Phi\theta + nc = \beta(P_1 - P_0)P_2$$

The manipulators spending c to purchase the stock is an equilibrium in this case if $P_2 > P_1$, that is, $\beta(P_1 - V) \geq \frac{nc}{P_1}$. The profit for each manipulator is $c(\frac{P_2}{P_1} - 1)$. Figure 2.A and Table 11 summarize the determination of the stock price in each period for this case.

TABLE 11 DEMAND FOR STOCK BY EACH GROUP OF INVESTORS AT EACH PERIOD.

This table summarize the determination of the stock price in each period for the high-attention case, where when $nc > \Phi(1-\theta)V$.

Period	Event	Price	Total demand of			
			Positive feedback investors	Loss aversion investors	Fundamental investors	Speculative manipulators
0	Public announcement of signal	$P_0^* = V$	0	$\Phi\theta$	$\Phi(1-\theta)$	0
1	Manipulators trade	P_1^*	0	$\Phi\theta(1-m(P_1^*))$	0	$\frac{nc}{P_1}$
2	Positive feedback investor trade	P_2^*	$\beta(P_1-P_0)$	$\Phi\theta(1-m(P_2^*))$	0	0
3	Dividend payoff	$P_3^* = V + \varepsilon$	$\beta(P_1-P_0)$	$\Phi\theta(1-m(P_2^*))$	0	0

The period between 0 and 1 is the pumping stage of the manipulation. The period between 1 and 2 is the dumping stage of the manipulation. The speculative manipulators unload all of their positions between these two dates. Finally, between 2 and 3, the stock price gradually reverts to the fundamental value. Figure 2.B shows the price dynamics for the two cases. The upper path represents the price dynamics for the high-attention events ($nc > \Phi(1-\theta)V$), and the lower path depicts the price dynamics for the low-attention events ($nc \leq \Phi(1-\theta)V$).

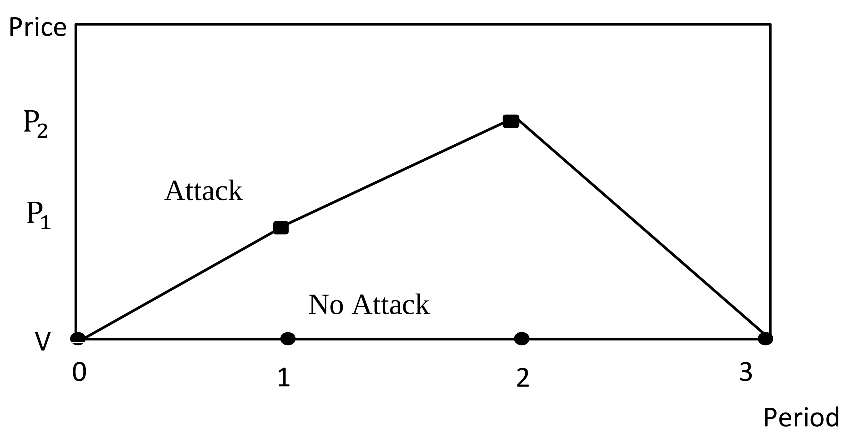

FIGURE 2.B PRICE DYNAMICS

This figure shows the price dynamics for the two cases. The upper path represents the price dynamics for the high-attention events ($nc > \Phi(1-\theta)V$), and the lower path depicts the price dynamics for the low-attention events ($nc \leq \Phi(1-\theta)V$).

Our model generates the following testable predications.

Prediction #1: Stocks with less mutual fund holdings are more likely to be manipulated.

Manipulation is an equilibrium outcome only if their total capital exceeds the value of shares held by fundamental investors ($\mathrm{nc} > \Phi(1-\theta)\mathrm{V}$). Mutual funds are usually fundamental investors, and they tend to sell their positions if the price is above the fundamental value. In that case, the manipulators have difficulty driving up the price significantly enough to attract the positive feedback investors. As a result, the stocks with a low mutual-fund holding value are more likely to be manipulated. [10]

Prediction #2: Stocks that experienced a recent decline in value are more likely to be manipulated.

Loss aversion investors are reluctant to sell a losing stock. As such, they are less likely to sell as long as the speculative manipulators have not bid the price above their average purchase cost. If the purchase cost for loss aversion investors is high, the speculative manipulators can more easily pump up the price without exploiting their own capital. We expect stocks with a recent decline in value to have loss aversion investors with higher costs. The proof of prediction #2 is in Appendix B.

After the initial run-up of the price, we expect to observe the reversal of the stock return for the manipulated stock. Meanwhile, the price increase in a stock with a positive fundamental surprise is sustainable in the long run. Because we cannot possibly detect the

[10] We use institutional holdings and mutual fund holdings interchangeably in this paper.

effect of trigger events on a one-by-one basis, we develop two cross-sectional predictions for the stock performance after the initial increase in price.

Prediction #3: After experiencing an extreme increase in price and trading volume, a stock with high mutual fund holdings outperforms one with low mutual fund holdings.

Prediction #4: After experiencing an extreme increase in price and trading volume, a stock with a recent increase in value outperforms one with a recent decline in value.

Predictions #3 and ***#4*** are derived from ***Predictions #1*** and ***#2***. A stock with a low mutual fund holding and a recent decline in value is more vulnerable to the manipulation. As such, the sudden increase in price and turnover is more likely to be the result of implicitly coordinated manipulation, as opposed to a positive fundamental surprise. We expect a manipulated stock to underperform after the manipulation phase.

The demand from each type of investors in our model also generates predictions about the speculative manipulators' trading patterns and returns when they pull off the implicitly coordinated manipulation schemes.

Prediction #5: Speculative manipulators tend to be the net buyers during the pump stage of the event and tend to be the net sellers during the dump stage of the event, while behavioral investors tend to trade in the reverse direction on an aggregate level.

Speculative manipulators are net buyers for the first day of manipulation when bidding the price up. However, they can be net sellers on the next day if they draw enough attention from the positive feedback investors. As such, they have an extremely short holding horizon.

Prediction #6: Speculative manipulators gain superior returns even though they trade excessively.

The model predicts that implicitly coordinated manipulation is an equilibrium only if the manipulation is profitable. We predict that speculative manipulators gain superior returns on their account.

II. Data Description

In this paper, we use two different databases in the empirical analysis. Stock-price data and mutual-fund holding data are obtained from the China Security Market and Accounting Research (CSMAR). Stock-price data include the date, stock ticker, opening price, closing price, highest and lowest price, trading volume in shares, trading value in RMB, number of tradable shares outstanding (floating shares), and the total number of shares outstanding for all of the stocks traded on a daily basis on the Shanghai Stock and Shenzhen Stock Exchanges from January 1, 2007, to March 31, 2013. These two exchanges in Mainland China both have a $\pm 10\%$ daily price limit (circuit breaker) for most stocks. The base price is the previous day's closing price. If the price limit is reached during trading, the trading can continue afterwards but never at a price exceeding the limit.[11] In this paper, we consider all Chinese A-share stocks traded in the two exchanges.

TABLE 12 SUMMARY STATISTICS ON FUND HOLDING OF A-SHARE STOCKS AND EVENT OCCURRENCE

Panel A shows the number of stocks for which these data are available at the end of each year from 2007 to 2012. We use the total fund holdings for each stock as a measure of the amount held by fundamental investors. Panel B shows the number of stocks hitting circuit breaker and experiencing abnormally high levels of trading volume.

Panel A: Summary on fund holding for each stock at the end of each year[12]				
Year	Number of A-share stocks traded in the two exchanges	Number of stocks with positive fund holding	Average fund holding of each stock (%)	Average number of holding funds of each stock
2007	1517	956	8.89	24.43
2008	1577	940	8.57	23.43
2009	1680	1278	6.2	22.17
2010	2020	1662	7.04	26.77
2011	2301	2060	5.56	27.54
2012	2456	2124	5.03	35.51
Panel B: Summary on occurrence of events				
Year	Number of stocks traded in the two exchanges	Number of stocks with events	Number of trading days with events	Total number of events
2007	1517	861	194	932
2008	1577	1159	211	1350
2009	1680	700	209	758
2010	2020	888	213	946
2011	2301	716	214	733
2012	2456	1151	233	1243
2007-2012	2491	2033	1274	5962

The mutual-fund holding (fund holding) data contains the number of shares held by each individual mutual fund on a semi-annual basis. Panel A in Table 12 shows the number of stocks for which these data are available at the end of each year from 2007 to 2012. We use the total fund holdings for each stock as a measure of the amount held by fundamental investors.

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[11] For stocks labeled as "special treatment stocks" or "ST", the daily price limit is ± 5%. The "ST" stocks are those stocks with negative accounting profits for two consecutive years or with the net asset value per share lower than the par value.

[12] The data for 2012 is on June 30th, 2012

Our trading data and daily portfolio holding data come from a national brokerage firm in China. The trading data contains the trading records of 1.8 million investors from January 2007 to October 2009. Our data set contains investors who trade common stocks, funds, treasury notes, and warrants. We focus on their trading records for common stocks, which is about 80% of all trading records. Detail description of this data set is at Section I of Chapter I.

Furthermore, to measure the abnormal returns around the events we identify, we use the abnormal return data provided by one of the largest fund management companies in China. The abnormal return is the daily return adjusted by a Barra-style risk model with style factors such as the market size, value, momentum, volatility, and liquidity and 29 industry factors for the China equity market.

III. Empirical Analysis on the Occurrence of Events and Stock Returns

To carry out the tests of our hypotheses, identifying the events that are likely to be subject to manipulation is essential. We propose to identify the events for manipulation based on the predictions from our model. After identifying the events, we look at the abnormal returns after the events for different types of stocks. We further study the trading patterns of the speculative manipulators and behavioral investors by using investors' trading records from a national brokerage firm in China.

A. Event Identification: hitting circuit breaker and experiencing abnormally high levels of trading volume

The financial press in China highlights stocks that reach their daily price limit after the market closes. To attract positive feedback trading, manipulators need to pump up the prices. Therefore, we look for extreme returns in the data. Moreover, according to theory, manipulated stocks also have abnormal trading volumes. To identify events that are likely to be manipulated, we look for stocks that hit their upper price limit of the 10% return and simultaneously have daily turnover that is more than twice that of their average daily turnover in the previous 120 trading days.

Since stocks sometimes hit the price limit several times within a short period of time, we identify each event as the first time in the last six months that a stock has reached the daily upper price limit. That is, if a stock has a 10% return and an abnormally high volume on both January 3 and January 5, we count it as one event on January 3, and we define this day with a 10% return as event day 0.

To allow for analysis on the abnormal return after each event, we consider all such events between January 1, 2007, and December 31, 2012. This period gives us a total of 5,962 events with 2,033 unique stocks and 1,294 unique event dates. The description of the occurrence of the events in each year is summarized in panel B of Table 12.

After we identify these events, we further sort all of the events into different groups by the two criteria discussed in section I of this Chapter.

Criteria 1: Total fund-holding value

According to Prediction #1, stocks with a low fund-holding value are more likely to be a victim of manipulation than stocks with a high fund-holding value. Fund-holding data are only available on a semi-annual frequency of June 30 or December 31 of each year. We calculate the fund-holding value as the multiplication of the percentage of shares held by all mutual funds and the market capital value at the end of the last half-year.[13] At the end of each half-year, we sort all of the stocks in the SHSE and the SZSE into quartiles based on the fund-holding value and match the fund-holding value of each stock to the events that occur in the subsequent six months. Since, for most years in our sample, the stocks with no fund holdings constitute more than 25% of the whole sample, we assign all of these stocks to quartile 1 and sort the remaining sample into three groups based on the fund-holding values.

Criteria 2: Previous gains

According to Prediction #2, the stocks with a previous decline in value are more likely to become victims of manipulation.

On the last trading day of each stock in each half-year, we calculate the volume-weighted price for the prior six months. Following Berkowitz, Logue, and Noser (1998), we calculate the average cost (volume-weighted average price) as:

[13] For all of the stocks for which their mutual fund holdings are not reported, we assign zero to the total fund holding value.

$$\text{Average Cost}_i = \sum_{t=1}^{T} \frac{P_{it}V_{it}}{V_{it}}$$

where P_{it} and V_{it} are the price and share volume at t days before the last trading day in each half year of stock i, and T is the total number of trading days of stock i during that half year. The price and volume used to calculate the average cost are adjusted by stock splits and dividend payouts. We use this measure of the average cost instead of an average cost calculated from an individual trading account for two reasons. First, the trading data in the record from the brokerage house only contain a fraction of all of the individual accounts and is only available for a shorter period of time (2007-2009). Second, and more importantly, the speculative manipulators need to rely on publicly observable measures to estimate the difficulty of the manipulation of a certain stock and coordinate among themselves. The volume-weighted average price is easily obtained by speculative manipulators, yet individual trading account information is not publicly available to the manipulators.

Using the closing price on the last trading day of each half-year, we calculate the gains of each stock in this half-year as

$$Gains_i = \frac{P_{i0} - Average\ cost_i}{P_{i0}}$$

where P_{i0} is the closing price on the last trading day in each half year. On each June 30 and December 31 between 2006 and 2012, we sort all of the stocks in the SHSE and the

SZSE into quartiles based on the gains during the past six months and match these quartiles of each stock to the events in the subsequent six months.

TABLE 13 SUMMARY STATISTICS STOCKS HITTING CIRCUIT BREAKERS AND EXPERIENCING ABNORMAL HIGH TURNOVER ON EVENT DAY

This table presents summary statistics of stocks in events between 2007 and 2012. Fund-holding value is the multiplication between percent of shares held by mutual funds and the market value of the stock at the end of the last half year. Gains is calculated with the closing price on the last trading day of the last half year and the volume-weighted average price in the six months in the last half year (excluding the last trading day). Total cap is the market value of equity at the end of last half year. Float is value of floating shares at the end of last half year. Average turnover is the average ratio between trading volume and tradable shares in the last 120 trading days before the event. Event turnover is the ratio between trading volume and tradable shares on event day 0. Abnormal turnover is the ratio of event turnover to average turnover. Mean and median are reported for each group.

Quartile	Stats	Closing price	Percent shares held by funds (%)	Fund holding value (Billion)	Gains (%)	Total Cap (Billion)	Float (Billion)	Average turnover (%)	Event turnover (%)	Abnormal Turnover
Sorted by Total Mutual Fund Holding Value										
Quartile 1 (Low)	Mean	9.76	0.01	0	-10.47	2.58	1.56	3.03	10.74	3.89
	Median	8.75	0	0	-9.52	2.07	1.26	2.67	9.38	3.29
	N	1700	1700	1700	1685	1700	1700	1700	1700	1700
Quartile 2	Mean	10.84	0.5	0.01	-12.88	3.25	2.08	2.74	9.93	4.04
	Median	8.89	0.31	0.01	-11.28	2.65	1.57	2.39	8.66	3.41
	N	1280	1280	1280	1278	1280	1280	1280	1280	1280
Quartile 3	Mean	13.26	3.3	0.11	-10.38	5.36	3.07	2.7	9.47	3.98
	Median	10.78	2.39	0.09	-10.53	3.82	2.27	2.38	8.18	3.31
	N	1493	1493	1493	1490	1493	1493	1493	1493	1493
Quartile 4 (High)	Mean	19.93	13.26	1.88	-3.32	23.67	10.52	2.03	6.87	3.78
	Median	15.76	10.84	0.82	-5.22	8.7	5.49	1.75	5.78	3.14
	N	1489	1489	1489	1487	1489	1489	1489	1489	1489
Sorted by Previous Paper Gains										
Quartile 1 (Low)	Mean	11.31	2.82	0.27	-21.6	6.59	3.79	2.55	9.22	3.99
	Median	9.23	0.65	0.02	-19.2	3.04	1.94	2.16	7.91	3.4
	N	1879	1879	1879	1879	1879	1879	1879	1879	1879
Quartile 2	Mean	11.39	3.05	0.32	-12.3	8.13	4.01	2.58	9.35	4.03
	Median	9.37	0.39	0.01	-10.2	3	1.98	2.21	8.07	3.45
	N	1590	1590	1590	1590	1590	1590	1590	1590	1590
Quartile 3	Mean	13.46	4.04	0.53	-5.51	10.14	4.48	2.69	9.25	3.86
	Median	10.69	0.89	0.03	-3.52	3.35	2.09	2.36	7.99	3.25
	N	1396	1396	1396	1396	1396	1396	1396	1396	1396
Quartile 4 (High)	Mean	19.97	8.84	1.12	12.3	11.21	5.38	2.78	9.15	3.65
	Median	15.08	4.48	0.18	12.0	4.41	2.65	2.38	7.53	2.98
	N	1075	1075	1075	1075	1075	1075	1075	1075	1075

Table 13 exhibits the descriptive statistics for the events in each quartile sorted by the fund-holding value and the previous gains. As expected, the stocks with a high fund-holding value have greater total capital and floating capital than stocks with a low fund-holding value. The stocks in quartile 4 with fund-holding values also tend to have lower average turnover and higher gains before the events. The four groups divided by the fund-holding value are similar in other dimensions. Different cutoff points for the fund-holding value generate similar results in the subsequent analysis, so we do not report these results for abbreviation.

The average turnover is uniformly decreasing in the gains quartiles and the higher fund-holding values (also total fund-holding percentage) are uniformly increasing in the gains quartiles. The stocks in the higher gains quartile are also slighter higher in total capital and floating capital. Stocks in the four quartiles sorted by the previous gains are similar in other dimensions.

B. Occurrence of Events

To confirm Predictions #1 and #2, we perform a logistic regression on the occurrence of events. We count each half-year of each stock in the SHSE and the SZSE as one observation. If an event occurs during a half year for a certain stock, we set the occurrence to one. Otherwise, the occurrence equals zero. Table 14 exhibits the logistic regression with the occurrence of events as the dependent variable and the total fund-holding value and previous gains quartiles as explanatory variables.

The results from all three model specifications are consistent with Predictions #1 and #2. In the baseline specification in the first column, only the holding value and gains quartiles are included. We use the quartile numbers for gains in the previous half-year as an explanatory variable to avoid the direct comparison in gains between different years. Since the Chinese stock market experienced overall extreme positive and negative returns over the sample years, the actual level of gains primarily captures the gain or loss in stock values over the years, instead of a cross-sectional comparison between stocks. Since we are trying to measure the reluctance of the loss aversion investors to sell a stock, we use the quartile number to compare this reluctance across different stocks.

TABLE 14 LOGISTIC REGRESSION ON THE OCCURRENCE OF EVENTS

This table presents the logistic regression of occurrence of events on fund-holding value and gains quartile. An event is defined as stocks hitting circuit breaker for one day and experience abnormal high turnover simultaneously. Each half year of trading between 2007 and 2012 of each stock traded in SHSE and SZSE is counted as one observation. Occurrence equals one if an event occurred in this half year for a certain stock. Average turnover is the average daily turnover in the previous half year. Amihud illiquidity measure is defined as average$\left(\text{abs}\left(\frac{daily\ return}{daily\ trading\ volume}\right)\right) * 10^6$ in the previous half year. White-robust t-stats are presented in parentheses.

	Base Model		Control for Semi-Year Fixed Effect		Control for Liquidity	
Total Fund-holding Value	-0.068	***	-0.053	***	-0.074	***
	(-3.785)		(-3.388)		(-3.914)	
Gains Quartile	-0.23	***	-0.25	***	-0.242	***
	(-16.286)		(-17.037)		(-16.338)	
Average Turnover					-0.052	***
					(-8.996)	
Amihud Illiquidity Measure					-0.020	
					(-1.101)	
Semi-year Fixed Effect	No		Yes		Yes	
Intercept	-0.592	***	0.49	***	0.648	***
	(-24.108)		(8.290)		(10.607)	
Pseudo R-squared	0.0137		0.0677		0.0718	
Number of Observations	21257		21257		21257	

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

Events are less likely to occur for stocks with high fund-holding values. Also, events are more likely to occur for stocks with low previous gains than for stocks that experience high previous gains. As shown in the second column, this effect is still significant after controlling for the half-year fixed effect.

One alternative explanation is that stocks with low liquidity tend to coincide with a low fund holding, and extreme return events tend to happen to low liquidity stocks. In the third regression, we show that the effect from the fund-holding value and the previous gains still exist after controlling for the average turnover and for the Amihud illiquidity measure of each stock in the previous half year (Amihud 2002). The t-statistics reported in Table 14 are adjusted by using White's robust standard errors.

C. Abnormal Return after Event

To study the return of manipulated stocks after events, we adopt the standard event study method in MacKinlay (1997). The cumulative abnormal return (CAR) of stock i on event day t is defined as:

$$\mathrm{CAR}(\mathrm{t}_1, \mathrm{t}_2) = \sum_{t=t_1}^{t_2} AR_{i,t}$$

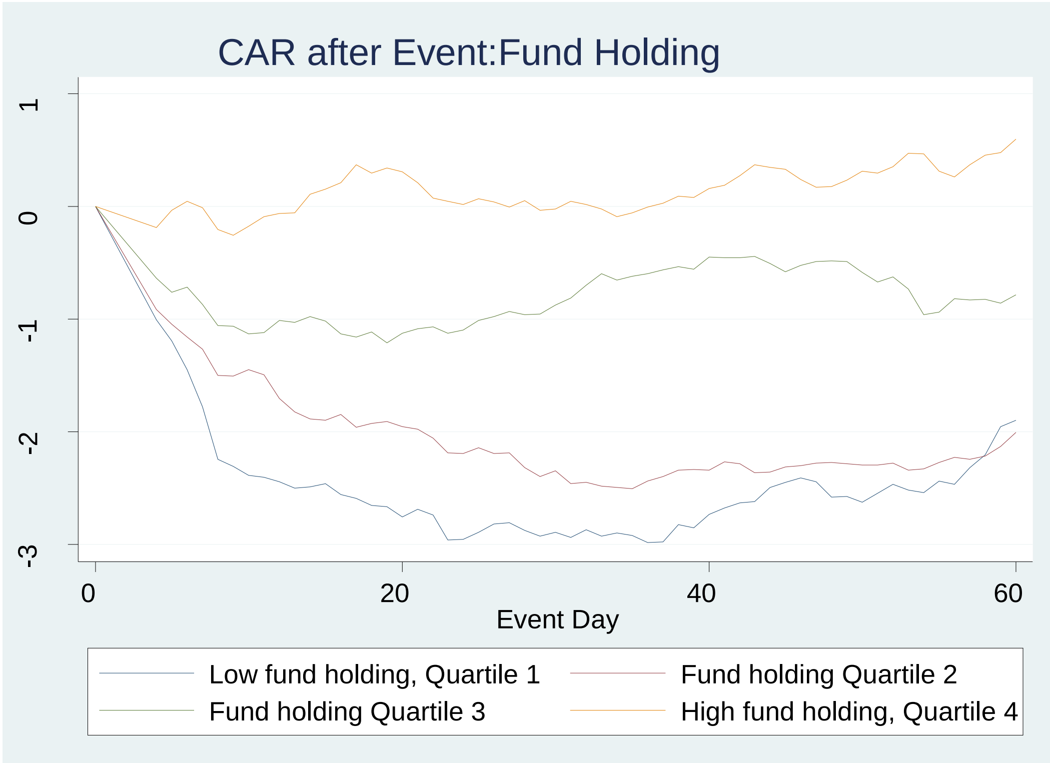
where $AR_{i,t}$ is the daily return adjusted by a Barra-style risk model with style factors such as market size, value, momentum, volatility, and liquidity and 29 industry factors for the China equity market.[14]

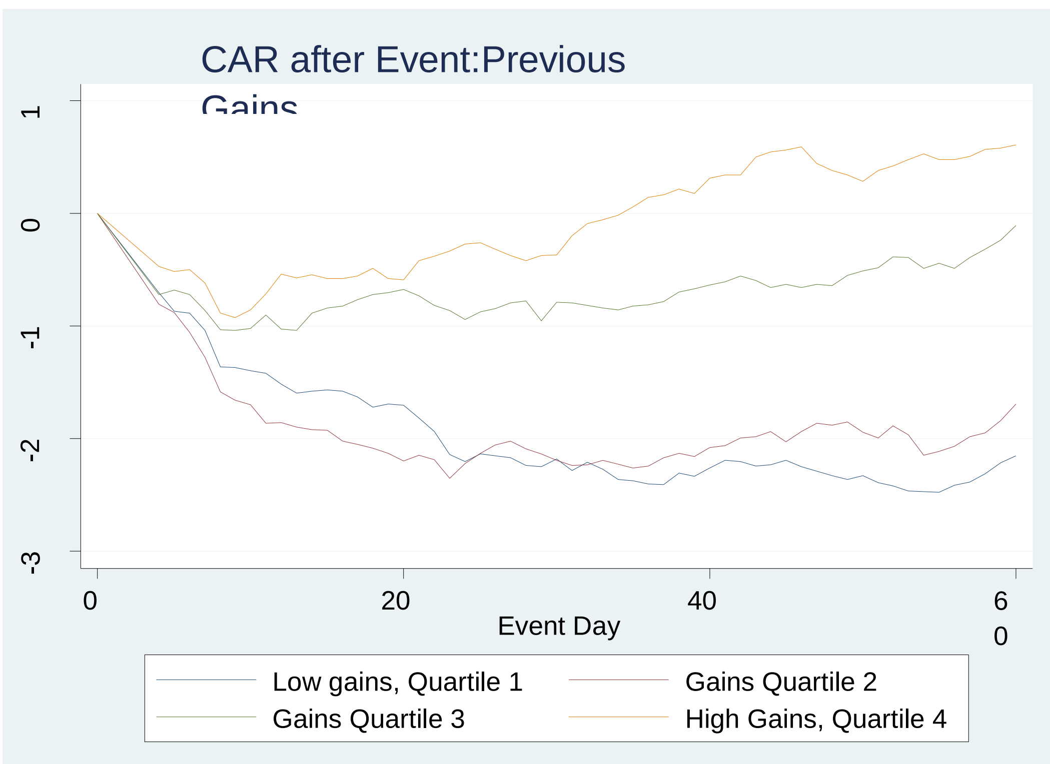
Since the manipulation event can last for multiple days, we define the first day after the event when the daily turnover is below the turnover on event day 0 as event day 1. Figure 3 displays the CAR for events from event day +1 to event day +60 for events in each quartile sorted by the fund-holding value and the gains, respectively. The result confirms Predictions #3 and #4.

[14] Abnormal return data is provided by one of the largest fund management companies in China.

FIGURE 3 CUMULATIVE ABNORMAL RETURNS AFTER TURNOVER DROPS

In the upper part, stocks are sorted by fund holding value. In the lower part, stocks are sorted by previous gains, Cumulative abnormal returns are calculated from the first trading day that daily turnover is below the event day turnover.


CAR after Event:Fund Holding
1
0
-1
-2
-3
0
20
40
60
Event Day
Low fund holding, Quartile 1
Fund holding Quartile 2
Fund holding Quartile 3
High fund holding, Quartile 4


CAR after Event:Previous Gains
1
0
-1
-2
-3
0
20
40
60
Event Day
Low gains, Quartile 1
Gains Quartile 2
Gains Quartile 3
High Gains, Quartile 4

As shown in the upper panel of Figure 3, the stocks with a low fund-holding value gradually decline in value within 60 trading days, yet stocks with a high fund holding value remain at a value similar to the value on event day 0. Similarly, stocks that experienced low recent gains underperform stocks with high recent gains substantially, as shown in the lower panel of Figure 3. [15] The significant reversal in price is consistent with the hypotheses that the initial run-up of price is partially due to manipulation.

Table 15 summarizes the CAR after the event (from event day +1 to event day +60). After the event, the stocks with a high fund-holding value have a cumulative return of -0.279% that is not significantly different from zero. Yet, the low fund-holding value stocks have an average CAR of -3.00% between event day +1 and event day +30. The difference in CAR between the two groups is -2.73% and significant at the 1% level for the same horizon. Moreover, the difference between the low fund-holding quartile and the high fund-holding quartile is significant for the CAR after 5 to 60 trading days.

Similarly, stocks with a previous gain in value have a cumulative return of 0.699% that is not significantly different from zero. Yet, the stocks with a previous loss in value have an average CAR of -2.964% between event day +1 and event day +30. The difference in CAR between the two groups is -1.99% and significant at the 1% level for the same horizon. Moreover, the difference between the low gains quartile and the high gains quartile is significant for the CAR after 5 to 60 trading days.

[15] Defining the event day in the conventional way (event day is set to one for the first trading day after the event, etc.) generates qualitatively the same result. Except for that the CAR is on average positive in the first trading day, consistent with the effect from positive feedback trading.

TABLE 15 CUMULATIVE ABNORMAL RETURNS AFTER EVENT DAY

This table presents the mean cumulative abnormal returns of stocks after events for various horizons. Abnormal returns are calculated by fitting a Barra style factor model. We collect stocks hitting circuit breaker and experience abnormal high turnover between 2007 and 2012. Stocks are sorted into quartiles based on fund-holding value, previous gains, asset float value, and percentage shares held by mutual funds. CAR of stocks in bottom quartiles and top quartiles, and difference between the two are reported in this table. P-values are presented in parentheses.

		5 Days		10 Days		20 Days		30 Days		60 Days	
By Fund Holding Value		Low Fund-holding Value									
	Mean	-1.116	***	-2.299	***	-2.769	***	-3.002	***	-2.021	***
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
		High Fund-holding Value									
	Mean	-0.04		-0.125		0.191		-0.279		-0.029	
	P-value	(0.713)		(0.526)		(0.496)		(0.422)		(0.952)	
		Difference in Mean									
	Difference	-1.077	***	-2.174	***	-2.96	***	-2.723	***	-1.993	***
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.002)	
By Previous Gains		Low Previous Gains									
	Mean	-0.921	***	-1.514	***	-2.128	***	-2.694	***	-2.689	***
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
		High Previous Gains									
	Mea	-0.412	***	-0.637	**	-0.632	*	-0.699		0.285	
	P-value	(0.006)		(0.017)		(0.091)		(0.133)		(0.644)	
		Difference in Mean									
	Difference	-0.509	***	-0.876	***	-1.496	***	-1.994	***	-2.974	***
	P-value	(0.006)		(0.006)		(0.001)		(0.000)		(0.000)	
By Asset Float		Low Asset Float									
	Mean	-1.264	***	-2.268	***	-2.683	***	-3.241	***	-2.185	***
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
		High Asset Float									
	Mean	-0.075		-0.254		-0.249		-0.418		0.476	
	P-value	(0.513)		(0.223)		(0.393)		(0.252)		(0.343)	
		Difference in Mean									
	Difference	-1.19	***	-2.014	***	-2.434	***	-2.822	***	-2.661	***
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
By Percentage Fund-holding		Low Percentage Share Holding by Funds									
	Mean	-1.246	***	-2.408	***	-2.725	***	-2.984	***	-1.719	***
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.001)	
		High Percentage Share Holding by Funds									
	Mean	-0.059		-0.111		0.094		-0.548		-0.226	
	P-value	(0.620)		(0.609)		(0.764)		(0.151)		(0.663)	
		Difference in Mean									
	Difference	-1.187	***	-2.297	***	-2.819	***	-2.435	***	-1.493	**
	P-value	(0.000)		(0.000)		(0.000)		(0.000)		(0.042)	

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level.

As a robustness check for Predictions #3 and #4, Table 15 also compares the CAR for the high or low total floating capital value of each stock and for the high or low fund-holding quartiles sorted by the percentage of shares held by the mutual funds. Consistent with the prediction from the model, the small stocks and low fund-holding percentage stocks both decline in value, whereas the large stocks and the high fund-holding percentage stocks do not decline in value after the same extreme return and volume.

Table 16 shows the cross-sectional regression result for the CAR on the total fund-holding values and the previous gains quartiles. All of the regression coefficients on the two variables are significant with the expected sign for all horizons. To further account for the change in the stock market condition through time, we add event half-year dummies to the regressions. The coefficients for the total fund-holding value and gains quartile are still significantly positive for all horizons.

In Panel C, the average turnover before the event and the Amihud illiquidity measure are added as controls for stock liquidity; and the abnormal turnover, defined as the event day turnover divided by the average turnover in the 120 trading days prior to the event day, is added as an explanatory variable. The CAR after the event is negatively related to the abnormal turnover on the event day. This is consistent with our model. Events with high abnormal turnover are more likely to be an event subject to manipulation by speculators.

TABLE 16 CROSS-SECTIONAL REGRESSIONS FOR LONG-RUN CAR OF STOCKS IN SAMPLE

This table represents the cross-sectional regression result of CAR on fund-holding value and gains quartile. Panel A is the baseline model with only fund-holding value and gains quartile as explanatory variables. Panel B controls for fixed effect of each half year. Panel C controls for stock liquidity and include abnormal turnover on the event day as an additional explanatory variable. Abnormal Turnover is defined as turnover on the event day divided by average turnover in the previous 120 trading days. White-robust t-stats are presented in parentheses. *** Significant at the 1 percent level, ** Significant at the 5 percent level.

Independent Variables	5 Days		10 Days		20 Days		30 Days		60 Days	
Panel A: Baseline Model										
Total Fund-holding Value	0.151	***	0.267	***	0.387	***	0.441	***	0.609	***
	(4.988)		(5.043)		(5.707)		(6.063)		(4.547)	
Gains Quartile	0.123	**	0.221	**	0.445	***	0.59	***	0.826	***
	(2.151)		(2.275)		(3.210)		(3.539)		(3.718)	
Intercept	-0.981	***	-1.75	***	-2.312	***	-2.822	***	-2.605	***
	(-10.440)		(-11.272)		(-10.665)		(-11.124)		(-7.451)	
Semi-year Fixed Effect	No		No		No		No		No	
Adj. R-Square	0.005		0.005		0.007		0.007		0.007	
Number of Observations	5939		5938		5937		5937		5921	
Panel B: Control for Semi-year Fixed Effect										
Total Fund-holding Value	0.15	***	0.277	***	0.392	***	0.428	***	0.56	***
	(4.979)		(5.203)		(5.780)		(5.946)		(4.208)	
Gains Quartile	0.13	**	0.228	**	0.438	***	0.58	***	0.833	***
	(2.272)		(2.331)		(3.141)		(3.462)		(3.729)	
Intercept	-0.99	***	-1.764	***	-2.305	***	-2.803	***	-2.589	***
	(-10.422)		(-11.203)		(-10.480)		(-10.912)		(-7.344)	
Semi-year Fixed Effect	Yes		Yes		Yes		Yes		Yes	
Adj. R-Square	0.011		0.01		0.011		0.01		0.015	
Number of Observations	5939		5938		5937		5937		5921	
Panel C: Control for Liquidity										
Total Fund-holding Value	0.134	***	0.248	***	0.355	***	0.395	***	0.535	***
	(4.663)		(4.918)		(5.313)		(5.560)		(3.997)	
Gains Quartile	0.132	**	0.221	**	0.421	***	0.553	***	0.805	***
	(2.307)		(2.252)		(2.998)		(3.272)		(3.586)	
Abnormal Turnover	-0.095	**	-0.282	***	-0.469	***	-0.518	***	-0.476	***
	(-2.546)		(-4.978)		(-5.693)		(-5.611)		(-4.191)	
Average Turnover before Event	-0.101	**	-0.175	**	-0.2	*	-0.165		-0.083	
	(-2.260)		(-2.328)		(-1.757)		(-1.100)		(-0.468)	
Amihud Illiquidity Measure	0.025		0.1107		-0.0317		0.154		-0.044	
	(0.310)		(0.701)		(-0.206)		(0.601)		(-0.185)	
Intercept	-0.348		-0.195		0.101		-0.314		-0.457	
	(-1.582)		(-0.552)		(0.189)		(-0.495)		(-0.601)	
Semi-year Fixed Effect	Yes		Yes		Yes		Yes		Yes	
Adj. R-Square	0.013		0.015		0.016		0.015		0.017	
Number of Observations	5939		5938		5937		5937		5921	

IV. Empirical Analysis on Trading Records

A. Trading Direction and Portfolio Return

We now focus on the trading behavior of speculative manipulators and behavioral investors during events. The anecdotal evidence suggests that wealthy individuals are the driving force for this type of manipulation. Unlike mutual funds, they are subject to little regulation on their investment. We treat individual accounts with more than 5 million RMB in equity as speculative manipulators. To the contrary, the previous literature shows that small individual investors tend to exhibit behavioral bias, such as loss aversion and positive feedback trading, when making their investment decisions. We suspect less wealthy individual investors are the victims to the implicitly coordinated manipulation. Therefore, we treat investors with less than 100,000 RMB in equity as behavioral investors. Following Barber and Odean (2008), the buy-sell imbalance of each type of investors for stock i on day t is calculated as:

$$\mathrm{BSI}_{\mathrm{it}}^{Investor\ Type} = \frac{\sum_j NB_{itj} - \sum_j NS_{itj}}{\sum_j NB_{itj} + \sum_j NS_{itj}}$$

where NB is the number of shares of stock i purchased by investor j at time t, and NS is the number of shares of stock i sold by investor j at time t. The buy-sell imbalance is calculated separately for speculative investors and behavioral investors, for each event day 0, and for each event day +1 respectively.

TABLE 17 INVESTORS' TRADING DIRECTION ON EVENT DAY 0 AND EVENT DAY +1

This table captures investors' pattern of manipulated stocks during and after manipulation. Speculative manipulators are defined as investors who hold portfolio over 5 million RMB in value. Behavioral investors are those who hold portfolios less than 100,000 in value. We use buy-sell imbalance to proxy for investors' trading direction of stocks. P-values are reported in parenthesis under the mean value.

	Low Institution Holding, Losing Stocks	High Institution Holding, Winning Stocks	Diff
	Panel A: During Manipulation (EventDay=0)		
	Speculative Manipulators		
Mean	0.265***	0.167***	0.098
	(0.000)	(0.000)	(0.170)
Median	0.719	0.332	
	Behavioral Investors		
Mean	-0.173***	-0.151***	−0.021
	(0.000)	(0.000)	(0.487)
Median	-0.173	-0.196	
Diff	0.438***	0.318***	
	(0.000)	(0.000)	
	Panel B: After Manipulation(EventDay=1)		
	Speculative Manipulators		
Mean	-0.226***	-0.094**	-0.132*
	(0.000)	(0.028)	(0.054)
Median	-0.585	-0.113	
	Behavioral Investors		
Mean	0.139***	0.079***	0.060**
	(0.000)	(0.000)	(0.012)
Median	0.147	0.107	
Diff	-0.367***	-0.173***	
	(0.000)	(0.000)	

*** Significant at the 1 percent level, ** Significant at the 5 percent level, * Significant at the 10 percent level

The results in Table 17 confirm Prediction #5 on the trading direction of investors. On average, speculative manipulators are net buyers during manipulation, and behavioral investors are net sellers. The direction flips sides for both types of investors on event day +1, the first trading day after the manipulators pump up the price. On event day 0, the difference in the buy-sell imbalance between the two groups of events is not significant. The result is consistent with the hypothesis that loss aversion investors tend to sell winners irrespective of whether there are potential changes in their fundamental values.

On event day +1, the speculative manipulators sell more shares of stocks with low fund-holding values and low previous gains as opposed to stocks with high fund-holding values and high previous gains, the difference is significant at the 10% level. The buy-sell imbalance is reversed for behavioral investors. They purchase significantly more shares of stocks with low fund-holding values and low previous gains than stocks with high fund-holding values and high previous gains. The difference between the two groups is significant at the 5% level for the behavioral investors.

B. Realized profit for speculative manipulators

Market manipulations are supposed to be profitable. Indeed, speculative manipulators realize significant gains by trading stocks with low fund-holding values and low previous gains between event day -1 and event day +1. The round trip return earned by the speculative manipulators is 2.95% (*t*-stat=3.30)[16]. Our analysis of the trading imbalance for the behavioral investors shows that they are net buyers of manipulated stocks on event day +1. They immediately suffer an unrealized loss of 1.89% (*t*-stat=4.54) on event day +2. If they hold on to the losing stocks, which they usually do, their unrealized loss reaches 2.52% (*t*-stat = 3.52) on event day +10.

V. Conclusion

In this paper, we provide an explanation for the phenomenon that the stock price and trading volume rise after news that is not related to a concrete change in the firm’s fundamental value. The phenomenon is pervasive in the Chinese A-share market, yet is rarely seen in developed stock markets.

[16] Our trading data contains the weighted average cost of stocks held by each investor on a daily basis. The realized gains of the speculative manipulators are calculated as the difference in selling prices and average costs over average costs. The unrealized gains of behavioral manipulators are calculated as the difference in closing prices and average costs over average costs.

We develop a model of trade-based manipulation in which a large number of speculative manipulators coordinate implicitly to exploit investors with behavioral biases. Because of the existence of investors with behavioral bias and the special stock-market environment in China, this new type of manipulation differs from those studied in the literature in several ways. The manipulation is not performed by a single manipulator or several manipulators with an explicit agreement. The manipulators coordinate implicitly after the observation of a public news event.

Successful manipulation does not rely on spreading false rumors or taking actions that change the value of the firm, which is illegal in a variety of stock markets. Moreover, no one in the market needs to be better informed than any other.

According to our model, we identify events that satisfy the key features of manipulation. We find empirical evidence consistent with the theoretical predictions on stock returns. The stocks with a low fund-holding and with a high average purchase cost among shareholders are more likely to be manipulated. After the initial run-up in price, these stocks experience reversals. Stocks with a low mutual-fund-holding value underperform stocks with a high mutual-fund-holding value by 2.73% in the 30 days after manipulation. The stocks with low previous gains prior to manipulation underperform stocks with high previous gains by 1.99% after manipulation. These results shed some light on the role of fundamental investors in a market dominated by individual investors. A certain level of mutual-fund-holding can provide stability for stocks in the sense that stocks with a high mutual-fund-holding value are less exposed to this type of manipulation.

The empirical evidence on super individual accounts is also consistent with the theoretical predictions. These accounts, which we suspect to be held by speculative manipulators, accumulate shares to pump the stock price initially and dump them after the significant rise in the price. Moreover, these accounts realize abnormally high returns during the days of manipulation. With this investor trading data, we provide evidence that speculative manipulators create attention-grabbing events by pumping up stock prices and make profits by leading behavioral investors to buy from them.

CHAPTER 3

SENTIMENT, DISAGREEMENT, AND IPO PRICING

The mispricing of a stock can exist as early as in the IPO process. This mispricing generally does not vanish until the delisting of the stock. As such, studying the mispricing of a stock from the first day of trading is of interest in order to examine its evolution afterwards. Indeed, there is an extensive line of literature on why IPOs are underpriced in the US stock market. Agency problems and information asymmetry are convincing explanations for IPO underpricing (Ritter 2011).[17] In this paper, instead of answering the question of why IPOs are underpriced, we test how the investor's sentiment and disagreement predict the cross-section of IPO underpricing.

An IPO first-day return is a commonly used indicator to evaluate its underpricing (Ritter 2011). The higher the IPO first-day return is, the more severely this IPO is underpriced. Recently, Baker and Wurgler's (2006, 2007) research on investor sentiment in the stock market has gained success in predicting the cross-section of stock returns. They predict that when market-wide sentiment is high, speculative and hard-to-value stocks receive higher relative valuations. Their empirical tests confirm that stocks with speculative and hard-to-value characteristics, such as young stocks, high-return volatility stocks, and unprofitable stocks, can earn lower subsequent returns when the prior sentiment is high.

A safe assumption is that some IPO stocks are more speculative and hard-to-value than others. However, empirically using Baker and Wurgler's (2006, 2007) theory to predict

[17] Ritter (2011) presents a recent survey on this line of research.

which IPO stocks are underpriced is challenging because of the endogenous issue and data restrictions. First of all, as noted in the "hot market" literature, IPO first-day returns, the number of IPOs, and the number of shares issued are successful proxies for the investors' enthusiasm for stock trading. Indeed, Baker and Wurgler (2006, 2007) construct a sentiment index that factors in the aforementioned three proxies. The endogenous issue occurs if we try to predict the IPO underpricing by using data on IPO activities. Secondly, a direct measure of the disagreement on IPO valuation is lacking. As pointed out in Baker and Wurgler (2007), analysts' earnings forecasts for a company is a natural indication of its valuation. The smaller the differences in forecasts, the easier the valuation of the stock is. Unfortunately, there are no analysts covering the earnings of IPO firms in the US market. These two issues make testing the effects of sentiment and disagreement on IPO first-day returns infeasible when using data from the US market.

We find several unique features of the Chinese stock market that make it better suited for testing Baker and Wurgler's (2006, 2007) theory on the role of investor sentiment in predicting the cross-section of IPO first-day returns.

First, the IPO issuance mechanism in the Chinese stock market solves the endogenous issue. In the United States, issuers usually time the market when deciding the IPO dates. However, firms in China do not have this privilege when going public. The IPO committee of the China Securities Regulatory Committee (hereafter CSRC) issues the IPO permissions after lengthy scrutiny. Many factors other than investor sentiment, such as the state economic development plan, the State-Owned-Enterprise reform goal, inflation rate, and GDP growth rate, affect the CSRC's decision on granting permits to pre-IPO firms. Theoretically, issuers and underwriters can choose a listing date six months after they receive the permission from the CSRC. In practice, they all decide to get listed as soon as possible without considering the market sentiment. The majority of them start trading within five business days of the CSRC's permission letters. Although bad for issuers in China, this mechanism significantly reduces the endogenous issue between sentiment and IPO activities in the Chinese stock market.

Secondly, analysts provide forecasts of the IPOs offer prices in the Chinese stock market. The analysts' predictions are a direct measure of the IPOs firms' valuations. Thus, we are able to estimate the dispersion of analysts' predictions to gauge how difficult discovering the true value of an IPO stock is for retail investors. We obtain the forecast data from WIND, a dominant and reliable financial data provider in China.

Last but not least, naive individual investors dominate the Chinese stock market. They usually have difficulty in discerning the fundamental values of stocks, but they are also attracted to the speculative appeal of IPOs. The first-day closing price of the IPOs may be significantly affected by their sentiment, especially when short sales of IPOs stocks are prohibited in the Chinese stock market.

Our testing produces two results. First of all, hard-to-value IPOs have higher first-day returns. We divide IPOs into three (five) portfolios by disagreement. The difference in the first-day returns of the hardest-to-value IPOs and those of the least hard-to-value IPOs is 54.47% (70.84%). These results are significant at the 1% level. This finding might be consistent with the disagreement model proposed by Hong and Stein (2007): in a market with short-sale constraints, disagreement fuels the trading among investors with positive views who bid the price up. We find that the first-day closing price is higher when the disagreement is greater in the Chinese stock market. The turnovers of IPOs on their first-day are 70% during our sample period.

Second, we find that the first-day returns of hard-to-value IPOs are even higher when the investor sentiment is high. We regress the first-day returns of the hardest-to-value IPOs on a sentiment index and known determinants of first-day returns and find that the coefficients on sentiment are positive and have 1% significance. In other words, there is a positive correlation between the first-day returns and investor sentiment. We repeat this exercise with portfolios consisting of less harder-to-value IPOs and we find the coefficients on sentiment are smaller. According to Baker and Wurgler (2006, 2007), hard-to-value stocks are overpriced more when market sentiment is higher. Our findings confirm that hard-to-value IPOs are more sensitive to investor sentiment than easy-to-value IPOs. Market sentiment further increases the dispersion of the first-day returns after the effect of disagreement.

Because, the Chinese stock market provides an ideal environment, we believe our results have general interest given the growing significance of this market. The Chinese stock market was ranked as one of the top-five IPO markets[18] and had the second-largest market capitalization among all national stock markets at year-end 2010.

[18] See Doidge, Karolyi, and Stulz (2011) for a summary of global IPO activities from 1990 to 2007.

The rest of the paper is organized as follows. Section I provides a review of the related literature. Section II describes the institutional setup of the Chinese IPO market and data. Section III presents the empirical results. Section IV reports the results from the robustness check. Section V concludes.

I. Literature Review

The underpricing of IPOs exists in the United States, China, and many other countries (Ritter 2011). There is a rich literature that studies why IPOs are underpriced. Our paper attempts to identify how sentiment and disagreement affect the magnitude of IPO underpricing or IPO first-day returns. Our paper is related to the research on factors that predict the cross-section of IPO first-day returns, which we briefly review here. Then we introduce the findings of sentiment's role in predicting cross-sectional returns, which has not been used to predict IPO first-day returns. Last but not least, we review the findings of the speculative nature of the Chinese stock market that is essential for sentiment and disagreement to gain predictive power in the IPO market.

A. Information and the IPO Market

Extending models in which underpricing is a compensation for uninformed investors who participate in IPOs, Carter and Manaster (1990) posit that high-quality issuers hire prestigious underwriters to signal to the market their low-risk characteristics, because prestigious investment banks have a reputation to maintain. Indeed, the authors find a significantly negative relation between prestige and the magnitude of IPO first-day returns.[19]

The book-building models (Benveniste and Spindt (1989) and Cornelli and Goldreich (2001)) assume that IPO underpricing is the cost to obtain a more accurate demand for the IPO stocks from institutional investors. If the offer price is so high that no money is left on the table, then institutional investors have no incentive to bid at all. Underwriters in the US IPO market, reward institutional investors who disclose their true valuation of the issuer's stock with disproportionately large allocations of shares. Aggarwal, Prabhala, and Puri (2002) find that there is indeed a positive relation between institutional allocation and first-day returns. In other words, IPOs with more institutional allocation earn higher first-day returns.

Ljungqvist and Wilhelm (2003) support the negative relation between an investment bank's pre-IPO equity holding and the first-day returns of IPOs. Their sample period is between 1996 and 2000, which is before and during the Dotcom Bubble. This is plausible because more informed investment banks benefit from higher offer prices on top of the fees earned.

B. *Investors Sentiment and the IPO Market*

Sentiment, as a bias borne by most investors, is useful for explaining bubbles and market crashes in the history of stock markets. Speculative and hard-to-value stocks draw investors' attention when investor sentiment is high, which might cause bubbles in asset

[19] This relation is sensitive to the period studied. Beatty and Welch (1996) find a positive relationship using data from early 1990s.

prices. However, when the sentiment is low, investors rush out to liquidate their holdings, causing market crashes. The rise and the burst of the Internet Bubble in the 1990s is an excellent illustration of investor sentiment's role in an extreme market fluctuation (Baker and Wurgler (2007)).

Baker and Wurgler (2006, 2007) show that speculative and hard-to-value stocks could be overpriced (underpriced) and earn lower (higher) future returns when investor sentiment is high (low).

Evidence also exists that proves investor sentiment's effect on IPO underpricing among developed stock markets. Studying a sample of more than 5,000 US IPOs from 1981 to 2009, Hrnjić and Sankaraguruswamy (2011) find a positive relation between aggregate investor sentiment and IPO underpricing. Darrien (2005) finds a positive relation among 12 French IPOs. Cornelli et al. (2006) extend the scope of study to 486 IPOs in 12 European countries and draw the conclusion that IPO underpricing is related to firm-level investor sentiment, instead of market-level investor sentiment. Dorn (2009) finds that IPOs attracting more individual purchases by investors exhibit higher first-day returns.

C. *Speculation in the Chinese Stock Market*

Empirical evidence demonstrates asset price bubbles generated by speculation in the Chinese stock and warrant markets. Mei et al. (2009) study the Chinese A-B share premium, which is puzzling since shareholders have the identical rights in dual-class shares. They find speculative trading of A-shares by domestic Chinese investors can explain the anomaly, because B shares were only allowed to be traded by foreign investors (mostly institutional investors) during their sample period.

Most recently, Xiong and Yu (2011) study the Chinese warrants bubble in which soon to expire, deep out of money, worthless warrants traded at substantially inflated prices with huge volume. They confirm that there was a speculative motive among Chinese investors that caused this bubble.

In the U.S. market, the average first-day return was about 17.6% between 1980 and 2011, with a historical high of 64.5% during the Internet Bubble. We find that the average first-day returns in the Chinese stock market are about 70% from 2005 to 2010. Thus, the average first-day return in the Chinese stock market is even higher than that of the U.S. market during the Internet Bubble. If there is a Chinese IPO bubble[20], one possible explanation is that the speculative trading among retail investors bid the price up in the Chinese stock market. The uncertainty of the IPOs' valuations certainly appeals to the speculative characteristics of Chinese retail investors.

II. Institutional Background and Data Description

A. IPO process in the Chinese stock market

Between January 1, 2005, and December 31, 2010, the Chinese stock market adopted a hybrid book-building procedure for IPOs.[21] There are several unique features to this procedure. First, the procedure consists of an offline soliciting stage and an online

[20] Existing behavioral literature shows that a bubble can rise due to, disagreement and short-sale constraints (Miller (1977) and Chen et al. (2002)), speculative trading (Scheinkman and Xiong (2003)), and positive feedback trading (Delong et al. (1990)).

[21] Fixed price and auction-like IPO allocations were implemented before 2005.

bidding stage. Only institutional investors can participate in the offline soliciting stage,[22] while both institutional and individual investors can participate in the online bidding stage. In other words, institutional investors can obtain IPO shares during both stages. The institutional investors' allotment received in the offline stage has at least a six-month lock-up restriction. However, shares obtained in the online stage can be sold on the first day. Second, the issuer and the underwriters determine the IPO offer price based on the institutional investors' bids. Winning institutional investors buy IPO shares according to the final offer price, not necessarily equal to their bidding prices. This offer price is also used for the online bidding by both institutional and individual investors. Third, the underwriters are not allowed to allocate more shares to institutional investors who disclose their true valuations of IPO stocks during the book-building process.[23] Institutional investors participating in the offline process receive the exact number of shares in their proposal. Fourth, the remaining shares are distributed to both institutional and individual investors through an online "lottery" system.[24] Investors have to pre-deposit funds into custody accounts designated for IPO stock purchases. If investors successfully win the IPO "lottery", the shares are transferred into their accounts. Unsuccessful bidders get refunds.

These features lead to the underpricing of IPOs in the Chinese stock market for the following reasons. First, institutional investors are motivated to bid a lower price during

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[22] At least 20 institutional investors have to bid during the process; otherwise the IPO process stalls.

[23] In the US market, underwriters allocate more shares to bidding institutions with higher prices as compensation for disclosing their true valuation.

[24] Approximately one week before the IPO, potential investors, including both institutional and individual investors, specify the number of shares they desire and deposit the equivalent fund into the designated bank account. In return, they receive a number of tickets for the later IPO "lottery". In the Shanghai Stock Exchange, one ticket represents 1,000 shares of subscription, while it represents 500 shares in the Shenzhen Stock Exchange.

the offline stage. Even if they lose the right to buy offline, they can still buy IPO shares during the online bidding. Indeed, the lower the offer price is, the more shares institution investors can afford. Second, as IPOs in China usually receive over-subscriptions, the exchanges have to draw the winning tickets. Only investors with the winning tickets receive the IPO shares at the offer price. The investors who can afford to subscribe to more IPO shares get more tickets, and hence have a higher chance of winning an IPO lottery. Indeed, institutional investors, who are much wealthier than retail investors, are much "luckier" in winning the IPO shares. Third, it is harder for individual investors to obtain IPO shares during the online stage because the success rate of the IPO lottery is extremely low. Those unlucky individual investors usually purchase IPOs on the first day, which eventually pushes the price up. Fourth, the persistence of IPO underpricing generates the positive feedback effect. On average, the opening price on the first day of each IPO during our sample period doubles the offer price. The closing price is even higher. Thus, institutional investors always have the motivation to set a lower offer price by collectively lowering their bids. Individual investors always want to fulfill their demand for IPO shares if they do not win the "lottery".

B. Data Description

We study IPOs between 2005 and 2010 in the Chinese stock market because of the hybrid IPO procedures.[25] We obtain return, volume, and financial data from the China Security Market and Accounting Research (CSMAR), the only data vendor in the

[25] After the reform, institutional investors are not allowed to participate in both the offline bookbuilding stage and the online bidding stage. The IPO offer prices are now set much higher than before because the institutional investors are competing with each other for the allotment from the offline stage. As a result, negative first-day returns appear more often in the market. Individual investors' demand towards IPO stocks is diminishing.

Chinese stock market accessible via WRDS. The first-day return is defined as the difference between the offer price and the first-day closing price. The turnover ratio is based on the total tradable shares.

WIND provides the analysts' forecasts about the IPO offer prices since January of 2005 when the hybrid book-building process was adopted. This data set also contains the affiliations of the analysts who provide the forecasts. We calculate the standard deviation for the analysts' forecasts for each IPO and use it as a proxy for the disagreement over the IPO valuation.

Table 18 provides the summary data for the IPOs from 2005 to 2010. The IPO offer prices, and P/E ratios generally seem to increase over our sample period. However, the number of IPOs and first-day returns fluctuate over the sample period.

We observe high first-day returns and huge turnover for IPO stocks in the Chinese stock market. The first-day average turnover is about 70%. To put this number into perspective, only 80% of the float is tradable on the first day. The other 20% of the shares is allocated to institutional investors during the offline book-building process and locked up for the next six months. Considering investors cannot sell shares they bought on the same day, we infer that the majority of investors who won IPO "lotteries" sell their holdings on the first day. This inference also implies that the demand for IPO stocks is constantly strong on the first day over our sample period. Considering the speculative nature of Chinese retail investors, this demand could come from the disagreement over valuation and market-wide sentiment.

TABLE 18 SUMMARY STATISTICS OF IPOS ACTIVITIES

This table presents average IPOs offer price, offer price earnings ratio, return and turnover ratio on the 1st day. 1st day return is the closing price divided by the offer price minus 1. Turnover ratio is total trading volume divided by all tradable shares.

Year	Number of IPOs	Offer Price	1st Day Return	P/E	1st day Turnover
2005	15	6.65	45.12%	21	57.14%
2006	66	8.15	84.81%	19	71.12%
2007	126	11.47	193.07%	27	64.56%
2008	77	11.95	114.87%	25	80.36%
2009	63	23.32	74.15%	36	79.31%
2010	232	29.40	44.56%	58	71.83%

III. Empirical Results

We first provide the results regarding the effects of the disagreement on the IPO first-day returns. The first-day closing price of the IPO stocks contains the true value of the stocks and the value of the option to sell the stocks the next day. Since the dispersion in opinion causes trouble for finding the fair value of the IPO stocks and make the option worth more, we expect that hard-to-value IPO stocks to close at a higher price.

There are different ways to measure the disagreement over a stock's valuation. As noted in Baker and Wurgler (2007), a common practice is to use dispersion in the analysts' forecasts and/or trading volume to measure the level of disagreement over the valuation. Here we obtain the analysts' forecasts on the lower and upper limit of the IPO offering price from the WIND database. And we calculate the dispersion with respect to the actual offering price as a proxy for the disagreement over the IPO stock value. With the increase in the dispersion of opinion, we observe the cross-sectional difference among the portfolio returns. Indeed, we observe a huge return difference (54%) between the hard-to-value and the easy-to-value IPO stocks. Although the average offer price is higher for IPOs with more disagreement, the relative pricing, that is, the M/B ratio, increases with the dispersion in opinion. Also, small stocks seem to not always be hard to value. We present our results in Panel A of Table 19.

TABLE 19 DISAGREEMENTS AND FIRST DAY TRADING

We divide IPOs between 2006 and 2010 into 3(5) portfolios ranking on analysts disagreement about offer prices. IPO 1st day return is closing price divided by offer price minus 1. Book value and earnings are data for the year prior to IPOs. Market capitalization is the product of closing price of the 1st day and number of tradable shares.

Panel A: 3 Portfolios

	Dispersion in Opinion			
	Low	Mid	High	H-L
IPO 1st day return	49.34	65.95	103.82	54.47***
IPO Offer Price	13.04	18.83	28.01	
Market/Book	5.79	4.88	2.88	
Price/Earnings	55.72	75.25	75.59	
Market Cap (in 1,000)	3,323	1,038	2,310	

Panel B: 5 Portfolios

	Dispersion in Opinion					
	Low		Mid		High	H-L
IPO 1st day return	41.20	59.90	64.94	82.75	112.04	70.84***
IPO Offer Price	11.72	15.56	18.46	21.31	30.90	
Market/Book	4.24	6.57	4.63	4.95	2.88	
Price/Earnings	51.20	64.61	76.78	69.06	80.06	
Market Cap (in 1,000)	3,990	1,961	1,184	1,079	2,837	

The literature well documents that IPOs underperform the market in the long run. We test whether disagreement over IPO valuations can predict the cross-sectional difference in the long-term cumulative abnormal returns of the IPOs. Table 20 presents the abnormal returns of three groups of IPOs sorted on disagreement under the CAPM and Fama-French three-factor models. The abnormal returns are cumulated over different horizons of up to one year. Consistent with the literature, we show that IPOs underperform in the long run in the Chinese stock market. Moreover, we find that the hard-to-value IPOs provide higher returns to investors over short horizons. However, the difference becomes insignificant when holding the stocks for one year.

TABLE 20 DISAGREEMENT AND LONG-TERM RETURNS

We divide IPOs between 2006 and 2010 into 3 portfolios ranking on analysts disagreement about offer prices. Abnormal return is the predicted value from the regression of portfolio returns using CAPM and Fama-French three factors model. Cumulative returns are calculated for different horizons.

	Dispersion in Opinion		
Cumulative	Low	Mid	High
Abnormal Return		Panel A: CAPM	
1 week	18.17%	27.88%	36.98%
2 weeks	32.57%	48.82%	66.19%
1 month	35.47%	62.07%	98.09%
3 months	2.78%	14.52%	43.19%
6 months	-30.41%	-27.06%	-12.54%
1 year	-75.58%	-73.56%	-73.26%
		Panel B: Fama-French three factors	
1 week	8.78%	12.04%	14.86%
2 weeks	16.44%	22.38%	25.25%
1 month	16.86%	22.33%	35.60%
3 months	-11.70%	-10.71%	2.27%
6 months	-39.84%	-42.74%	-35.64%
1 year	-79.07%	-78.33%	-78.55%

Hong et al. (2006) model a negative relation between a bubble's size and the asset float and predict that bubbles are larger when the asset float is limited. In the time-series domain, the price of IPO stocks drops after the lock-up restriction expires for the insiders and institutional investors. We observe that the cumulative excess returns become negative around six months, which is the length of the lock-up in the Chinese stock market.

We now turn our focus to the effect of market sentiment on IPO pricing. Baker and Wurgler (2006, 2007) find a cross-section difference between hard-to-value (speculative, divergence in opinion) stocks and easy-to-value (safe, convergence in opinion) stocks under the fluctuation of market sentiment. Baker and Wurgler (2006, 2007) show that when investor sentiment is high, speculative stocks are overpriced and hence earn a low future return. Because some IPO stocks are harder to value and hence are more speculative, we expect that investor sentiment generate a bigger bubble on those speculative stocks.

To facilitate the analysis, we first have to build an investor-sentiment index for the Chinese stock market. The number of IPOs and the new shares issued in the IPOs are two important proxies for the investor-sentiment analysis because they represent the underwriters timing the market and catering to investors. Unfortunately, we are unable to use these two IPO related proxies in this analysis.

Considering the lesser connection between IPO activities and investor sentiment, we propose an alternative proxy: units issued by open-end funds. Open-end funds were introduced to China investors in 2001 as investment vehicles managed by sophisticated professionals. Although more and more empirical evidence shows open-end fund managers do not have superior stock picking abilities, they are good at catering to the market. Fund managers will issue new funds when they sense investor sentiment is high.

Furthermore, we also use the closed-end fund discount, market turnover (excluding IPO stocks), new stock trading accounts, and the Consumer Confidence Index (CCI) when measuring investor sentiment in the Chinese stock market. We standardized all of the variables before performing any further analysis.

To filter out the macroeconomic shock to investor sentiment, we also regress the above five sentiment indicators on macro-variables, including the growth of the industry's product (IAV), CPI, PPI, and MBCI. However, we find poor explanatory power between the macro-variables and the sentiment indicators. As such, we perform a principal component analysis on the five sentiment indicators directly and use the coefficients for the first principal component in forming the investor-sentiment index.

The sentiment index is a time series. Thus we match the IPO first-day return with the sentiment value on the listing date. We also add factors related to the first-day returns: proceeds and firm age.[26] For each of the 579 IPOs during 2005 to 2010, we regress their first-day returns on the market sentiment for their listing dates, IPO proceeds, and firm age. We repeat this analysis for the three groups of IPOs sorted on disagreement levels.

Panel A in Table 21 presents the regression results for the different portfolios sorted on disagreement. To begin with, we find the coefficients for investor sentiment are all significantly positive over the different levels of disagreement. This finding confirms our conjecture that investor sentiment increases IPO first-day returns. Moreover, we observe that the coefficient on sentiment increases monotonically with respect to the level of disagreement. This finding confirms the conjecture that speculative stocks are more prone to overpricing when investors sentiment is high.

IV. Robustness Check

In the above section, we sort IPOs into three portfolios based on the level of disagreement. Here we repeat our analysis with a smaller group. We sort the IPOs into five portfolios based on the level of disagreement. The results are qualitatively similar for all analyses. We present our results in Panel B of Table 19 and Panel B of Table 21.

[26] Due to the difference between the book-building process in the US market and the hybrid book-building process in the Chinese stock market, we do not include factors related to the reputation of underwrites and the institutional ownership prior to the IPOs.

TABLE 21 DISAGREEMENT, SENTIMENT AND DETERMINANTS OF IPO FIRST-DAY RETURNS

We divide IPOs between 2006 and 2010 into 3(5) portfolios ranking on analysts disagreement about offer prices. We explain the cross-sectional differences of IPOs 1st day returns using sentiment, proceeds, and age. Sentiment is a time-series index, compositing of units issued by open-end funds, close-end fund discounts, market turnover, new stock trading accounts, and consumer confidence index. Proceeds is calculated as the natural log of funds received by issuers. Age is the difference between IPO date and foundation date. White-robust t-stats are presented in parentheses.

Panel A: 3 Portfolios

Independent Variables	Dispersion in Opinion		
	Low	Mid	High
Sentiment	12.51***	13.48***	26.62***
	(7.55)	(7.04)	(13.40)
Proceeds	-15.33***	-23.79***	-27.22***
	(-6.23)	(-5.46)	(-6.53)
Age	-0.0035**	0.0000	-0.0019
	(-2.15)	(0.02)	(-0.63)
Intercept	278.43***	386.76***	461.83***
	(7.91)	(6.72)	(8.20)
Adj. R2	0.361	0.363	0.537

Panel B: 5 Portfolios

Independent Variables	Dispersion in Opinion				
	Low		Mid		High
Sentiment	6.5170***	11.2228***	17.8183***	20.5429***	26.5153***
	(2.63)	(8.04)	(4.45)	(7.93)	(10.65)
Proceeds	-12.2701***	-17.1525***	-25.9736***	-33.1838***	-24.9602***
	(-4.13)	(-4.18)	(-4.77)	(-5.07)	(-0.84)
Age	-0.0036*	-0.0046*	0.0012	-0.0001	-0.0034***
	(-1.79)	(-1.84)	(0.39)	(-0.03)	(-5.10)
Intercept	228.6378***	308.7658***	412.3284***	522.6236***	441.0856***
	(5.21)	(5.55)	(5.76)	(5.95)	(6.63)
Adj. R2	0.206	0.453	0.323	0.506	0.533

*** Significant at the 1% level. ** Significant at the 5% level.* Significant at the 10% level.

V. Conclusion

Traditional finance theory shows which stocks achieve higher first-day returns, that is, hard-to-value stocks reward investors more than easy-to-value stocks do as they bear the risk of information asymmetry. By incorporating the investors' sentiment fluctuations, we extend this line of research by answering the question of when do hard-to-value IPOs get hotter and even become bubbles.

There are two major obstacles keeping us from answering this question with US data. In US markets, IPO underpricing is a well-accepted proxy for investors' sentiment, which causes an endogenous issue. Also, the lack of the analysts' coverage of IPO stocks makes it impossible to reasonably measure the disagreement over IPO valuation. On the contrary, IPOs in the Chinese stock market are granted by the regulator without considering investor sentiment. We also obtain a unique database with analysts' predictions of IPO offer prices in the Chinese stock market. The dispersions in these forecasts reflect the magnitude of disagreement.

Our empirical results show that hard-to-value IPOs achieve higher first-day returns when the market sentiment is higher. This is consistent with the findings in Baker and Wurgler (2006). The difference lies in that their testing applies to listed stocks. We extend their reasoning to IPOs.

Appendix A: The case of Zhejiang Dongri

In this appendix, we present another typical case of implicitly-coordinated manipulation, the case of Zhejiang Dongri (hereafter "ZJDR"), a real estate firm incorporated in Wenzhou, China. The firm has 5% stock holding of Bank of Wenzhou, a small local bank with minimal value compared to ZJDR.

On March 28th, 2012, Chinese State Council assigned the city of Wenzhou to status of a 'Comprehensive Pilot Financial Reform Zone'. This is the only zone of this kind in China. Wenzhou, a coastal city, which already has the most vital private owned enterprises in China, is regarded by the market as the spearhead of financial sector liberalization in China. With the news reaches the market; it draws collective attention of speculators.

Right after the policy announcement, "ZJDR"'s price rose from 6.6 RMB to 17.4 RMB during April 2012, a 160% monthly return, which is the top performer in that month. The average daily turnover is 16% in the meantime. To put this set of number in perspective, we note that the average monthly return was 7% and the average turnover is 2.32% in A-share market during April 2012. Excluding trading days in 2012, "ZJDR" reports an average monthly return of 0.7% and average monthly turnover of 1.33% since listing. Figure 5 presents the change of volume and price of "ZJDR" in year 2012.

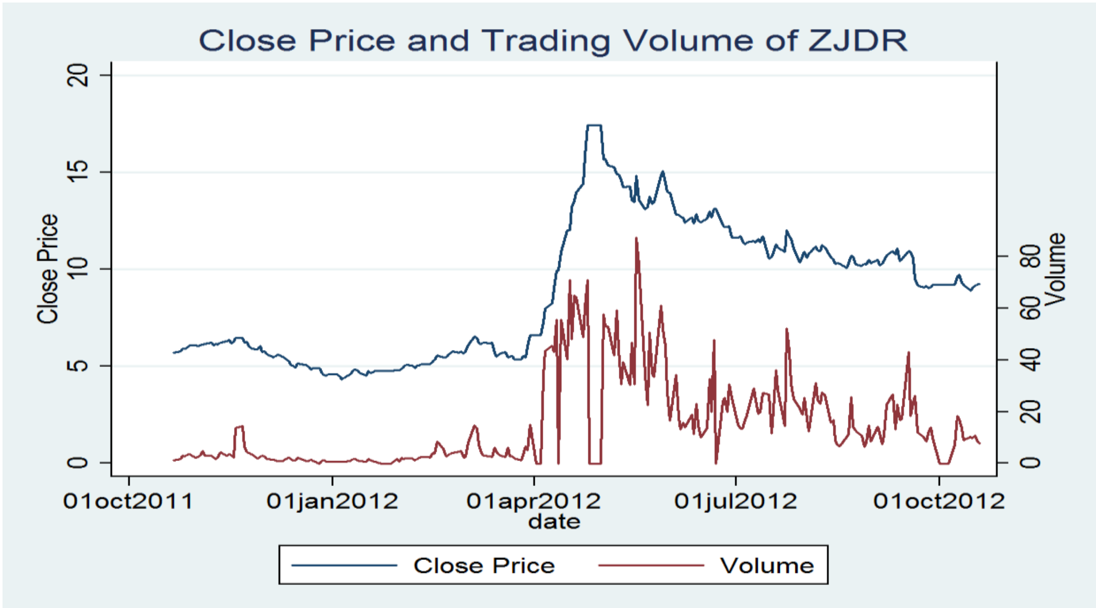

FIGURE 4 STOCK PRICE AND TRADING VOLUME OF ZJDR

This figure presents the change of volume and price of "ZJDR" in year 2012. Right after the policy announcement on March 28, 2012, "ZJDR"'s price rose from 6.6 RMB to 17.4 RMB during April 2012. The price and volume slide down-ward after the Board's clarification that there is no change in firm's fundamentals. "ZJDR" closes at 11.62 RMB as of June 29, 2012. In other words, those who bought "ZJDR" in April suffer a loss of 33% in 3 months.

The month long roar of price and trading volume drew attention of China Securities Regulatory Commission (hereafter "CSRC"). CSRC is the market authority in China and plays similar role as SEC in the US market. They monitor the market closely. CSRC halts ZJDR's trading for 3 days at the end of April and request the Board of ZJDR to announce any information that might cause the abnormal activities of its stock. The board of "ZJDR" issued a statement on the last trading day of April 2012, clarifying that there is no under-disclosed events or secrets. More specifically, the management team has no plan to undertake asset reorganization, SEO, M&A, or etc., in the future.

This statement probably cooled down enthusiastic investors. The price and turnover slide down-ward after the Board's clarification. "ZJDR" closes at 11.62 RMB as of June 29, 2012. In other words, those who bought "ZJDR" in April suffer a loss of 33% in 3 months.

Appendix B: Proof of prediction #2

For two distribution function of loss aversion investors' purchase cost, $\mathrm{m}^{\mathrm{a}}(\mathrm{P})$ and $\mathrm{m}^{\mathrm{b}}(P)$, if $\mathrm{m}^{\mathrm{a}}(\mathrm{P})$ first order stochastic dominates $\mathrm{m}^{\mathrm{b}}(P)$, then $\mathrm{P}_1^{\mathrm{a}} > \mathrm{P}_1^{\mathrm{b}}$ and $\beta(\mathrm{P}_1^{\mathrm{a}} - V)\mathrm{P}_1^{\mathrm{a}} > \beta\left(\mathrm{P}_1^{\mathrm{b}} - V\right)\mathrm{P}_1^{\mathrm{b}}$. The condition for manipulation to be an equilibrium is $\beta(\mathrm{P}_1 - \mathrm{V})\ \mathrm{P}_1 \geq\ nc$, as derived in the solution to the model. Therefore, given the same level of attention triggered by the event (n) and the amount of capital held by each manipulator (c), the condition is more likely to be satisfied when the distribution function is $\mathrm{m}^{\mathrm{a}}(\mathrm{P})$.

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