Wealth Redistribution in Bubbles and Crashes*

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Abstract

We take the perspectives of ordinary people—investors, pensioners, savers—and examine a novel aspect of the social impact of financial markets: the wealth-redistribution role of financial bubbles and crashes. Our setting is that of the Chinese stock market between July 2014 and December 2015, during which the market index rose 150% before crashing 40%. Our regulatory bookkeeping data include *daily* holdings and transactions of *all* investors in the Shanghai Stock Exchange, enabling us to examine wealth redistribution across the entire investing population. Our results reveal that the ultra-wealthy, those in the top 0.1% of the wealth distribution, actively increase their market exposures—through both inflows into the stock market and tilting towards high beta stocks—in the early stage of the bubble period. They then aggressively reduce their market exposures shortly after the market peak. Relatively poor investors exhibit the exact opposite behavior. Our estimates suggest a net transfer of over 200B RMB from the poor to ultra-wealthy over this 18-month period, or 30% of their initial account value. Further analyses suggest that our result is unlikely driven by investors' rebalancing trades and is more consistent with differential investment skills.

Keywords: bubbles and crashes, wealth inequality, real effects, social impact

1. Introduction

Financial markets have gone through repeated episodes of bubbles and crashes. Historical examples include the Dutch tulip mania in the 17^{th} century, the Mississippi and South Sea bubbles in the 18^{th} century, and the 'Roaring 20s' in the 20^{th} century. More recently, the NASDAQ index rose nearly threefold in the late 1990s before crashing 75% by the end of 2000; real estate prices in major US cities experienced a historical boom which ended in the 2008 global financial crisis. Bubbles and crashes are by no means unique to developed markets. The Chinese stocks market, for example, soared more than 150% in the second half of 2014 and first half of 2015, and gave up much of that gain in the next few months.

The repeated emergence of extreme price movements—large upswings followed by precipitous drops—has long intrigued economists. Prior literature has focused primarily on the formation of bubbles and possible triggers for crashes: for example, the frictions/constraints or behavioral biases that are necessary to generate bubbles; the groups/types of investors that are likely behind the initial price rally and subsequent corrections; whether and how arbitrageurs trade against or ride the bubbles.

Relatively little is known, however, about the social consequences of bubbles and crashes. Indeed, a popular view in the literature is that financial markets are a side show and have a negligible impact on the real economy. Indeed, Morck, Shleifer, and Vishny (1990) and Blanchard, Rhee, and Summers (1993) argue that the "irrational" component of stock valuation does not affect real investment. This view seems naturally applicable to bubble episodes: take the Internet bubble for example, by the end of 2000 the Nasdaq index fell virtually to its pre-bubble level; moreover, the increased investment in the tech sector during the four years of the Internet Bubble is largely consistent with improved productivity in the sector (see, e.g., Pastor and Veronesi, 2009).[1]

In this paper, we take the perspectives of ordinary people—investors, pensioners, savers, etc., and examine a novel aspect of the social impact of financial markets, one that has received little attention in academic research until recently: the wealth redistribution role of financial bubbles and crashes. As shown by Piketty (2014, 2015), there has been a worldwide surge in wealth inequality in both developed and developing nations over the past half a century, a big part of which can be attributed to small but persistent differences in investment returns between the poor and wealthy.[2] As a natural extension to this line of argument, we set out to understand the impact of financial bubbles and crashes—during which both market volatilities and trading volume peak (so much more potential for wealth transfers)—on the distribution of household wealth.[3]

The extant empirical literature on bubble-crash episodes have explored detailed trading records of a small subset of investors (e.g., Brunnermeier and Nagel, 2004; Greenwood and Nagel, 2009; Griffin, Harris, Shu, and Topaloglu, 2011; Liao and Peng, 2018), or individual sell transactions (without the accompanying buy transactions) of the entire US population from tax-return filings (e.g., Hoopes et al., 2017). The fact that prior researchers are only able to observe a non-representative subset of the investor universe

[1] More recently, after the 2008 global financial crisis, there is a renewed interest in the impact of leverage-fueled bubbles and crashes on the health and functioning of the banking sector, and its indirect impact on the real economy.

[2] Both the popular press and academic research have since linked this widening wealth inequality to adverse social outcomes, including social unrest, political populism, regional crimes, and mental health issues (e.g., Wilkinson and Pickett, 2018).

[3] For example, Sir Isaac Newton, one of the greatest scientists in human history and a lifelong investor, lost his lifetime savings of £20,000 in the South Sea Bubble (worth over £4M today) and had to file for bankruptcy.

(be it hedge funds, mutual funds or households), or a part of their transactions (sells but not buys) makes it difficult, if not impossible, to analyze the issue emphasized in this paper—wealth redistribution across the whole investor population.

Some recent studies, using administrative data (usually at an annual frequency) of holdings by the full population of Northern European countries, have provided evidence that the rich indeed get richer through financial investment in calm market conditions (see, for example, Bach, Calvet, and Sodini, 2018; Fagereng, Guiso, Malacrino and Pistaferri, 2018).[4] However, the low-frequency nature of the data renders them ill-suited to study the impact of bubbles and crashes on wealth redistribution. For one thing, bubble episodes can emerge and change directions quickly. Second, bubble-crash episodes are often accompanied by elevated trading activity; observing household holdings with annual snapshots is likely to yield an incomplete (perhaps misleading) picture of the impact.

We contribute to the debate on this issue—the societal impact of financial-market bubbles and crashes—by exploiting *daily* regulatory bookkeeping data from the Shanghai Stock Exchange that cover the *entire* investor population of roughly 60M accounts. Relative to the data used in prior studies, our regulatory bookkeeping data offer two unique advantages. First, our data contain individual accounts' holdings and trading records, at the firm level, at a daily frequency. Second, the holdings of all investors in our sample sum up to exactly each firm's total tradable shares; likewise, the buy and sell transactions in our sample sum up to the daily trading volume in the Exchange. The granularity and completeness of our data enable us to track the exact amount of capital

[4] A large part of this wealth redistribution can be attributed to persistent differences in both individual risk preferences and investment skills—the wealthy are usually more risk tolerant and have better access to information than the poor.

flow across different investor groups in the market, as well as the resulting gains and losses.

For ease of computation, we aggregate the 60M accounts into various investor groups. At a broad level, we classify all accounts into three categories: those owned by households, institutions, and corporations.[5] The first two categories account for roughly 25% and 11% of the total market value, but 87% and 11% of the total trading volume, respectively. The last category includes both holdings by private firms and government-sponsored entities; it accounts for the majority (64%) of the market value but has little trading activity (2%). Within the retail category, we further divide all accounts into five groups based on the aggregate account value (equity holdings in both the Shanghai and Shenzhen Stock Exchanges + cash) with cutoffs at RMB 100K, 500K, 3M, and 10M.[6] Based on estimates from Piketty, Yang and Zucman (2018), these cutoffs roughly correspond to the 50th, 90th, 99th, 99.9th percentile of the wealth distribution in China, respectively.[7]

Our datasets cover an extraordinary period—from July 2014 to December 2015—during which the Chinese stock market experienced a rollercoaster ride: the Shanghai Composite Index climbed more than 150% from the beginning of July 2014 to its peak at

[5] We further divide institutional accounts into 19 groups based on the types of institutions following commonly used classifications (e.g., mutual funds vs. banks).

[6] For accounts that existed before July 2014, wealth classifications are done at the end of June 2014 and are kept unchanged throughout the sample. For accounts that were opened after July 2014, we classify these new accounts every six months. For example, for accounts opened between July and December 2014, we classify them into five groups on December 31, 2014.

[7] Since we do not observe households' non-stock investment, we are effectively providing a lower bound of their total financial wealth. For example, households with over 10M RMB in their stock accounts are almost certainly above the 99.9th percentile of the wealth distribution.

5166.35 on June 12th, 2015, before crashing 40% by the end of December 2015.[8] We naturally divide our sample period into two subperiods: a boom period that spans July 2014 to June 2015 (including a mild increase from July to October 2014 and a rapid rise from October 2014 to June 2015), and a bust period spanning June to December 2015. This bubble-crash episode offers us a unique opportunity to analyze the incremental impact of bubbles and crashes on wealth redistribution across the investing population (compared to the relatively calm market in the first four months of our sample).

The gains/losses during this 18-month period can be attributed to two sources: a) the initial wealth allocation in the stock market, and b) capital flows into and out of the market during the 18-month period. Textbook portfolio-choice models postulate that the initial allocation can be determined by a number of factors: investors' total financial wealth, risk aversion, and return/risk expectations. Since our dataset does not include non-stock investment (e.g., investment in Treasury, housing markets), we do not have much to say about the heterogeneity across investor groups in their initial capital allocation decisions. As a result, we focus squarely on the gains and losses generated by capital flows during this period.[9]

Given the extreme market movement during our sample period, we start our analyses focusing on investors' market timing activity. That is, we assume that every RMB invested in the stock market tracked the market index (i.e., ignoring the heterogeneity in portfolio compositions). At the most aggregate level, the three investor

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[8] Major financial media around the world have linked this incredible boom and bust in the Chinese stock market to the growing popularity, and subsequent government crackdown, of margin trading in China.

[9] Another reason that we want to abstract away from the initial capital allocation is that its effect on final wealth is conceptually trivial – which is simply the product of the initial allocation and the cumulative portfolio return over the entire period.

sectors—households, institutions and corporations—have positive capital flows of RMB 1.2T, 110B, and 100B, respectively, into the stock market during the bubble period. A large part of this inflow, about 1.1T RMB, can be mapped to the conversion of restricted shares owned by corporations (mostly state-owned enterprises and government entities) into tradable shares in late 2014 and early 2015. (The remaining 300B RMB is due to firm equity issuance.) We observe a vastly different pattern in the crash period: households in aggregate have a capital outflow of 720B RMB, while institutions and corporations increase their stock holdings by 170B and 1.2T RMB, respectively, partly due to the government bailout of the stock market.[10]

Since we are primarily interested in wealth redistribution across households with different initial wealth levels, and the household sector alone accounts for nearly all the trading volume in the market (85%), we next zoom in (focusing exclusively) on the five household groups.[11] More specifically, we adjust daily capital flows of each household group by a fraction of the aggregate daily flow of the entire household sector, proportional to the capital weight of each group at the beginning of our sample. Consequently, daily "adjusted flows" of the five household groups, designed to capture active relocations into (or out of) the stock market beyond their initial capital weights, sum up to exactly zero. Doing so also allows us to more easily compare across household groups, which have different aggregate account value at the beginning of our sample.

[10] A number of state-owned institutions and government-sponsored investment vehicles were instructed to buy stocks in the second half of 2015, in a coordinated effort to sustain the market.

[11] Although we do not observe individual households' investment in mutual funds and hedge funds, we believe that the impact of such delegated management on the household wealth distribution is negligible. The cumulative flow to the fund sector from the beginning of our sample to the market peak is -80B RMB, which is dwarfed by the same-period household sector inflow to the market of over 1.2T RMB.

An interesting, perhaps surprising, pattern emerges from the data. In the bubble period, especially early in the runup, wealthier households allocate more capital to the stock market; indeed, there is a positive *monotonic* relation between account value and capital flows into the market for the period July 2014 to June 2015. Interestingly, as soon as we enter the crash period, we see the exact opposite pattern in capital flows: larger household accounts are now net sellers of stocks, while smaller accounts are net buyers. There is again a monotonic, but negative, relation between account value and capital flows to the stock market.

Since the wealthier households get into the market in the early stage of the bubble and exit quickly after the market peak, while the smaller accounts do the exact opposite, there is, not surprisingly, a wealth redistribution from the smaller accounts to the larger ones. Wealth transfers across the five household groups are computed as adjusted flows multiplied by subsequent market returns, so sum up to exactly zero in each day. For example, from July 2014 to December 2015, the smallest two household groups experience an aggregate loss of 103B RMB, while the largest household group experience a gain of 95B RMB. Nearly all this transfer is accrued after October 2014 – in the period of extreme market movements.

To further capture the heterogeneity in investor portfolio choice (and the resulting wealth implications), we conduct similar exercises at the stock level. Specifically, we define *benchmark* daily flows to a stock in the following way: a) just like our earlier exercise at the market level, each household group contributes a constant fraction (proportional to each group's initial capital share) to the total capital flow of the entire household sector and b) households invest their new capital across stocks according to their initial portfolio weights. We then calculate daily adjusted flows in individual stocks for each household group by subtracting the benchmark flow from the actual flow.

In the bubble period, the wealthier groups move into high-beta stocks while the smaller accounts tilt toward low-beta stocks; there is once again a monotonic relation between account value and the average beta of net purchases by each group. We again see the exact opposite pattern during the bust period: the wealthier groups now move away from high-beta stocks, and the smaller accounts are net buyers of high-beta stocks. These patterns are consistent with what we see at the market level: larger household accounts, relative to the smaller ones, seek market exposures in the bubble period (especially early in the bubble), and quickly reduce their market exposures in the early stage of the crash.

After accounting for heterogeneity in stock holdings, the smallest two household groups experience a net loss of 246B RMB from July 2014 to December 2015, while the wealthiest household group experience a net gain of 232B RMB; again, nearly all this transfer is accrued after October 2014. Together with the market-level result, these figures suggest that about half of the total wealth redistribution is due to aggregate flows into (out of) the market, and the other half to the wealthy's better stock selection relative to the poor.[12] To put these numbers in perspective, the aggregate holding value of the bottom two household groups is 840B RMB at the end of June 2014, so the cumulative loss in this 18-month period amounts to 29% of their initial account value. On the flip side, the

[12] Part of the wealthy's stock selection ability can be attributed to their time-varying beta exposures of the risky portfolio—which is another way of market timing. The rest of the difference in stock selection is likely driven by the wealthy's information advantage over the poor in the cross-section of stocks.

aggregate holding value of the wealthiest household group is 770B RMB at the beginning of our sample period, so a net gain of 30%.

Finally, we interpret our findings through the lens of a stylized portfolio-choice model. In particular, we allow different household groups to have different exposures to stock market movements through their non-stock investment (e.g., human capital), which with realistic assumptions can generate part of the trading pattern we observe through investor rebalancing. However, such rebalancing-motivated trades can only account for a negligible fraction of the wealth transfer across investor groups.

Consequently, we argue that the majority of the wealth redistribution from the poor to ultra-wealthy in our sample is consistent with heterogeneity in investment skills.[13] Conceptually, it is conceivable that the ultra-wealthy have better access to information on both aggregate market movements and idiosyncratic stock returns than the poor. Empirically, while trades by the poor negatively forecast stock returns in the cross-section, those by the ultra-wealthy positively predict stocks returns. Moreover, our documented wealth redistribution is concentrated in periods with substantial market movements (after October 2014) and in stocks with high volatilities. Therefore, a key takeaway from our paper is that the heterogeneity in investment skills is amplified in bubble-crash episodes, when both market uncertainty and stock volatilities are at their peaks. As such, our results speak more generally to wealth redistribution resulting from financial investment: while bubbles and crashes occur infrequently, they can contribute substantially to the rising concentration of household wealth.

[13] This is consistent with the findings of Fagereng, Guiso, Malacrino and Pistaferri (2018).

2. Related Literature

Our results contribute to the literature on wealth redistribution between the poor and rich (and the ultra-wealthy) in their financial investment. Bach, Calvet, and Sodini (2018) and Fagereng, Guiso, Malacrino, and Pistaferri (2018), using administrative data of household financial investment in Northern European countries, find that the wealthiest 1% of the population earn an annual investment return that is a full-percentage point higher than the rest of the population. Given the low-frequency nature of the data, these studies focus on buy-and-hold portfolio returns over a long period of time. Campbell, Ramadorai, and Ranish (2018), exploiting individual stock market investment data from India, also show that the rich get richer (and poor get poorer) due to differences in portfolio diversification. Our study complements and extends the prior literature by examining the role of financial investment in driving wealth inequality in bubble-crash episodes. From a methodological perspective, while prior studies draw primarily on investors' differences in buy-and-hold returns in normal market conditions, we instead focus on the gains and losses resulting from investors' *active* reallocation decisions in periods with extreme market movements.

Our paper also contributes to the understanding of investor portfolio choice—particularly their buy and sell decisions—in financial bubbles and crashes. Brunnermeier and Nagel (2004), Greenwood and Nagel (2009), Griffin et al. (2011) and Liao and Peng (2018) show that more sophisticated investors ride the bubble and get out of the market shortly before the crash, while less sophisticated investors get into the game too late and appear to be the ones driving the overshooting. More recent studies, for example, Dorn and Weber (2013) and Hoopes et al. (2017), using proprietary data in Germany and the US respectively, find that the wealthy (the poor) tend to be net sellers (buyers) of stocks during the global financial crisis. While our results on investor trading activity are consistent with these prior studies, we emphasize the wealth redistribution between the poor and wealthy using our comprehensive daily holdings/transaction data.

Finally, our study contributes to the recent debate on income and wealth inequality. Atkinson, Piketty, and Saez (2011), Alvaredo, Atkinson, Piketty, and Saez (2013), Piketty (2014, 2015), and Piketty, Yang, and Zucman (2018) provide compelling evidence that there is a worldwide surge in wealth concentration in the last fifty years, a part of which may be attributed to the high returns enjoyed by capital owners. Our paper provides direct evidence for this capital-investment channel. The ultra-wealthy, those in the top 0.1% of the wealth distribution, have both larger risk tolerance and better access to information than the rest of the population; consequently, they enjoy a disproportionate share of the total return on capital. This effect is further amplified in financial bubbles and crashes (when market volatility peaks), leading to an even higher degree of wealth concentration.

3. Institutional Background and Data Descriptions

The last two decades have witnessed tremendous growth in the Chinese stock market. As of June 2015, the total market capitalization of China's two stock exchanges, Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE), exceeded 10 trillion USD, second only to the US. Despite this unparalleled development, China's stock market exhibits many defining features of a developing market. For example, it remains dominated by retail investors; according to the official statistics released by the Shanghai Stock Exchange, retail trading accounted for over 85% of the total trading volume in 2015.

We obtain daily regulatory bookkeeping data from the Shanghai Stock Exchange, which cover the entire investor population of roughly 60M accounts. More specifically, our account-level data are compiled by the China Securities Depository and Clearing Corporation and are sent to the Exchange at the beginning of each trading day. The data are kept on the Exchange's internal servers for record keeping purposes. Relative to the data used in prior studies, our regulatory bookkeeping data offer two unique advantages. First, our data contain individual accounts' holdings and trading records, at the firm level, at a daily frequency. Second, the holdings of all investors in our sample sum up to exactly each firm's total tradable shares; likewise, the buy transactions and sell transactions in our sample sum up to the daily trading volume in the Exchange.

Account holdings in each stock are then aggregated to pre-specified investor group level. Overall, there are three investor categories in the market: retail investors, institutional investors, and corporations. Retail investors are further stratified based on their account values. Specifically, we take the maximum portfolio value (including equity holdings in both Shanghai and Shenzhen exchanges, as well as cash) in the previous one year and assign each household to one of the following five wealth groups: below 100k RMB (WG1), 100k - 500k RMB (WG2), 500k - 3 million RMB (WG3), 3 million -10 million RMB (WG4), and above 10 million RMB (WG5).

For accounts that existed before July 2014, the classification is done on June 30th, 2014, and is kept constant throughout the sample period. In other words, wealth fluctuations during the bubble-crash episode do not affect households' group assignments.

For accounts that were opened after July 2014, we classify these new accounts into the same five wealth groups every six months. For example, for accounts opened between July and December 2014, we classify them into five groups on December 31, 2014.

Investors in our sample collectively hold a market value of 13T RMB on July 1st, 2014; this rises to a peak of 34T on June 12th, 2015 and falls to 24T at the end of 2015. On average, corporations hold 64% of the market value, institutions hold 11%, and households hold the remaining 25%. Although owning most of the market, corporations seldom trade and account for only 2% of daily trading volume; retail investors, in contrast, contribute 87% of daily volume. Within the household sector, at the beginning of our sample (July 2014), the capital weights of the five groups (in increasing order of wealth levels) are 12%, 17%, 29%, 16%, and 26%, respectively. Table 1 reports the summary statistics of the account value, capital weight, and trading volume of all investor groups.

4. Capital Flows and Wealth Transfers

This section presents our main empirical results on how different investor groups trade/allocate capital in a bubble-crash episode, as well as the resulting wealth transfers across investors.

4.1. Capital Flows by Different Investor Groups at the Market Level

We start our analysis by examining capital flows into and out of the whole market by different groups of investors. Specifically, the capital flow to each stock s by investor group g on day t is calculated as the change in stock holdings from the beginning to the end of the day multiplied by the closing price:

$$flow_{g,s,t} = (shares\ held_{g,s,t} - shares\ held_{g,s,t-1}) \times price_{s,t}. \quad (1)$$

Summing across all stocks in the market, we get:

$$flow_{g,t} = \sum_{s} flow_{g,s,t}. \quad (2)$$

By definition, the total capital flow, summed across all investor sectors, is equal to the aggregate increase of tradable share supply in the market. During our sample period of July 2014 to December 2015, the increase of tradable shares in the whole market amounts to 2.1T RMB, of which 1.6T is due to conversion of restricted shares initially owned by corporations into tradable shares, and the remaining 0.5T due to firm IPOs, SEOs, and conversion of convertible bonds.

Figure 1 shows an anatomy of cumulative daily capital flows by different investor sectors—households, institutions, and corporations. From July 1st, 2014 to June 12th, 2015, the household sector has a cumulative inflow of 1.2T RMB, while the other two sectors have cumulative inflows of 110B and 100B, respectively. Household inflows keep rising until July 1st, 2015, at a peak of 1.3T RMB. Short after that, the household sector starts to sell their shares to corporations, mainly government-sponsored investment vehicles. These government-related entities are instructed by financial regulators to "sustain" the market after one of the worst crashes in the Chinese stock market history. By the end of December 2015 (relative to the market peak on June 12), corporations have a cumulative inflow of 1.2T RMB, while the household sector has an outflow of 900B.

We then zoom in and focus on capital flows of the household sector. Figure 2 shows the cumulative (unadjusted) daily flows of the five household groups. There is a monotonic *positive* relation between account value and capital flows during the boom period. Household Group 5 allocate the most capital to the stock market in the boom and start this capital reallocation from the very beginning of our sample. On the other extreme, Group 1 investors actually reduce their allocation to the stock market during the boom. The other three groups of households are somewhere in the middle. At the market peak on June 12th, 2015, the five groups, from the smallest to the largest in terms of account value, have cumulative flows of -219B, 103B, 294B, 291B, and 724B, respectively. After the peak, the wealthy quickly exit the market, selling their shares partly to smaller households who come to the game relatively late. In the bust period of June to December 2015, the five groups have capital flows of 5B, 39B, -123B, -187B, and -457B, respectively.

One potential concern with unadjusted RMB flows is that these five household groups have different wealth levels to begin with. Moreover, besides capturing trading across household groups, which is the focus of our analysis, these unadjusted flows also reflect buying and selling with the other two investor sectors. Consequently, we adjust capital flows of each household group by subtracting a fixed fraction of the total flow reported by the entire household sector, where the fraction is proportional to the capital share of the corresponding group at the beginning of the sample:

$$Adj\_flow_{g,t} = flow_{g,t} - \omega_g \Big(\sum_g flow_{g,t}\Big), \quad (3)$$

where ω_g is the initial capital share of investor group g in the stock market. In other words, the benchmark case we consider is one in which all household groups expand their stock investment at the same rate. Adjusted flows therefore capture excessive relocation into and out of the market and, by construction, sum up to zero across different household groups for each day.

Figure 3 shows cumulative adjusted flows by different household groups. Again, we see a monotonic positive relation between account value and adjusted flows. The two wealthiest groups of households are net buyers, while the smaller households are net sellers of stocks during the bubble period. The cumulative adjusted flows of the wealthiest (WG5) and second wealthiest (WG4) groups peak on June 3rd and May 25th, 2015 at 410B and 108B RMB, respectively, a few weeks before the market peak (June 12th, 2015). On June 12th, the cumulative adjusted flows of the five groups, in increasing order of account value, are -358B, -104B, -46B, 99B, and 408B, respectively. The wealthier groups then begin to exit the market shortly after the market peak. In a little over two months, from Jun 12th to Aug 26th, the Shanghai Composite Index has dropped from a peak of 5166 to a trough of 2927. During this period, the adjusted flows of the five groups are 110B, 214B, 118B, -78B, -363B, respectively. In other words, by the time the market has reached its bottom, the wealthier groups have already pulled out a large part of their inflows accumulated in the boom period. The market then rebounds to close at 3539 on December 31st. From the peak to the end of our sample, the five household groups have cumulative adjusted flows of 89B, 164B, 84B, -70B, -265B, respectively.

4.2. Flow-Generated Gains and Losses at the Market Level

After documenting the flow pattern of household groups during the bubble-crash episode, we then turn to analyzing the resulting gains and losses. Given the extreme market movement in this period, we first focus on the gains and losses that can be attributed to market timing activity. In other words, we assume every RMB invested in the market tracked the market index. Flow-generated gains at the market level are then calculated as the product of daily flows and subsequent market index returns. Specifically, the cumulative flow-generated gain up to day t for investor group g is equal to:

$$cum\_flow\_gen\_gains_{g,t}^{mkt} = \sum_{\tau \le t} flow_{g,\tau} \times ret_{\tau,t}^{mkt}, \quad (4)$$

where $flow_{g,\tau}$ is the capital flow of group g in day τ, and $ret_{\tau,t}^{mkt}$ is the cumulative market return between τ and t. Similarly, cumulative adjusted-flow-generated gains are calculated as:

$$cum\_adj\_flow\_gen\_gains_{g,t}^{mkt} = \sum_{\tau \le t} adj\_flow_{g,\tau} \times ret_{\tau,t}^{mkt}. \quad (5)$$

Figure 4 shows the cumulative flow-generated gains for the three broad investor sectors: households, institutions, and corporations. While the latter two sectors experience relatively flat gains/losses, the household sector accumulates a capital gain of 582B RMB as of the market peak on June 12th, 2015, which then quickly turns into a 40B loss in the second half of 2015.

Figure 5 zooms in on the household sector and shows the cumulative flow-generated gains for the five household groups based on account value. For the entire one-and-half-year period, the five household groups accumulate capital gains of -55B, -60B, -26B, 17B, and 85B, respectively. After adjusting for the part of flows that is proportional to the group's initial capital weight, we show in Figure 6 that the cumulative adjusted-flow-generated gains for the five household groups are -50B, -53B, -15B, 23B, and 95B. This amounts to a roughly 100B RMB wealth transfer from the smallest two groups to the wealthiest group.

For reference, in the first four months of our sample—July to October 2014—when the market experiences a mild increase, the amount of wealth transfer is much smaller in magnitudes—the cumulative flow-generated gains for the five household groups in this four-month period are -2B, -2B, -2B, 0, and 3B, respectively. (The corresponding figures are -2B, -2B, -1B, 0, and 4B for adjusted-flow-generated gains.) This suggests that extreme market movements, relative to periods of calm market conditions, amplify wealth redistribution from the poor to wealthy.

4.3. Capital Flows and Flow-Generated Gains and Losses at the Stock Level

To capture the heterogeneity in portfolio choice, in this subsection, we examine the capital flows and resulting gains and losses at the stock level for each household group. Stock-specific flows are calculated using equation (1). To calculate adjusted flows *in individual stocks* for each household group, we define the stock-level benchmark flow in the following way: a) each household group receives a constant fraction of the total capital flow of the entire household sector in each day (proportional to each group's initial capital share), and b) households invest their new capital in the stock market according to their initial portfolio weights. Just like assumption a), assumption b) is also intended to control for the impact of initial portfolio decisions. Consequently, adjusted flows by group g in stock s can be defined as:

$$Adj\_flow_{g,s,t} = flow_{g,s,t} - \omega_g (\sum_g flow_{g,t}) w_{g,s}, \quad (6)$$

where $w_{g,s}$ is the initial portfolio weight of group g in stock s.

To track wealth transfers among investor groups, similar to the exercise in Section 4.2, we calculate stock-specific flow-generated gains for each household group by interacting daily flows (both actual and adjusted) to the stock with subsequent stock returns. We then sum this number across all stocks in the portfolio to derive the total gains and losses for each household group. More formally, we define flow-generated gains by group g as:

$$cum\_flow\_gen\_gains_{g,t} = \sum_{s} \sum_{\tau \le t} flow_{g,s,\tau} \times ret_{s,\tau,t}. \quad (7)$$

Similarly, cumulative adjusted-flow-generated gains are defined as

$$cum\_adj\_flow\_gen\_gains_{g,t} = \sum_{s} \sum_{\tau \le t} adj\_flow_{g,s,\tau} \times ret_{s,\tau,t}. \quad (8)$$

Figure 7 shows cumulative flow-generated gains for the three broadly defined investor sectors. Cumulative-flow-generated-gains earned by the household sector peaks at 420B RMB on June 8th, 2015, before turning into a 203B RMB loss at the end of 2015. Compared with the corresponding numbers in Section 4.2 (582B in gain and 40B in loss), households as a whole lose from stock selection in this period.

Figures 8 and 9 present the cumulative-flow- and cumulative-adjusted-flow-generated gains of various household groups, after accounting for portfolio heterogeneity. Based on unadjusted flows in the entire period, the five household groups have cumulative gains of -116B, -161B, -133B, -2B, and 209B, respectively. These figures become -105B, -141B, -101B, 16B, and 232B, respectively, based on adjusted flows. In short, there is a wealth transfer of over 200B RMB from the two smallest groups to the wealthiest group in a window of merely 18 months. Half of this transfer is attributable to the variation in market timing activity, while the other half is due to heterogeneity in investor portfolio choice. Relative to the groups' aggregate account value at the beginning of our sample, this wealth transfer amounts to a 29% loss of the initial account value for small investors, and a net gain of 30% for the wealthiest group.

For ease of comparison, Table 2 lists all the estimates (discussed above) of capital flows and flow-generated gains at both the market and stock levels for different investor groups and over different horizons. For instance, Panel B reports flow-generated gains/losses in the first 4 months of our sample vs. the subsequent 14 months (calm vs. extreme market conditions). Nearly all of the wealth transfer we document is accrued in the post-October 2014 period. Panel C then divides all stocks into quintiles based on return volatilities (after adjusting for firm size).[14] There is a monotonically increasing relation between stock volatilities and investor gains and losses. Stocks in the top quintile of return volatilities alone account for nearly half of the 200B wealth transfer between the poor and ultra-wealthy.

5. Interpretations of Our Findings

We have so far examined heterogeneity in households' stock market investment, and the resulting gains and losses experienced by various household groups. In this section, we interpret our findings through the lens of a simple, stylized portfolio choice model.

Consider an investor (household) i with total financial wealth $W_{i,t}$, and a power utility function with risk aversion γ_i. There exists one risky asset (i.e., the stock market portfolio), whose return in the next period follows a log-normal distribution, with a (subjective) expectation of $\mathrm{E}_{i,t}(R_{i,t+1})$, and a conditional variance of σ_t^2. (Implicitly, we assume that investors do not disagree about the market variance, which can be precisely measured.) The risk-free rate in the economy is R_f. The myopic demand for the risky asset can be approximated by (see Campbell and Viceira, 2001):

$$D_{i,t} = \frac{\mathrm{E}_{i,t}(R_{i,t+1}) - R_f}{\gamma_i \sigma_t^2} W_{i,t}. \qquad (9)$$

[14] Specifically, we first regress stock return volatilities on firm size and then sort stocks based on the residual volatilities.

It is clear from the above expression that the initial amount of capital allocated to the stock market can be determined by an array of factors: an investor's total financial wealth ($W_{i,t}$), her risk aversion (γ_i), subjective expectation of future market returns ($\mathrm{E}_{i,t}(R_{i,t+1})$), and conditional variance of the market (σ_t^2), all measured at the beginning of the period. Given that these factors are unknown to outside observers—in particular, since we do not observe investors' total financial wealth (which includes investment in all other financial markets)—we choose to abstract away from investors' initial capital allocation, and focus solely on capital flows (or capital reallocation) in calculating gains and losses in our sample.

5.1. Rebalancing Trades

An obvious reason that investors move in and out of the stock market is for rebalancing. As the market value changes, an investor's portfolio weight in risky assets may deviate from her optimal weight. Further, given the varying degrees of exposures to equity markets through their other investment, different investors face different rebalancing needs. To illustrate, imagine an investor whose other investment (e.g., human capital) is weakly correlated with the stock market, an increase in stock market value leads to an overweight in stock investment and therefore an incentive to downsize her stock portfolio. On the other hand, for an investor whose other investment (e.g., own business) is strongly correlated with the stock market and who also borrows to finance his investment, a rise in market value leads to a smaller exposure to the stock market and therefore an incentive to increase her stock holdings.

To a first approximation, such rebalance-motivated trades are proportional to market movements. Consequently, the law of motion of an investor's investment in the stock market can be expressed as:

$$W_{j,t} = W_{j,0}(1 + r_{j,1}\alpha_j)(1 + r_{j,2}\alpha_j) \dots (1 + r_{j,t}\alpha_j). \qquad (10)$$

where $W_{j,t}$ is investor j's investment in the stock market in period t, $r_{j,t}$ is investor j's portfolio return in period t, and α_j is investor j's time-invariant propensity to rebalance (which depends on her exposures to the equity market through her other investment). We estimate α_j for each household group using daily $W_{j,t}$ and $r_{j,t}$ from the entire 18-month period. Rebalance-motivated trades on day t are then equal to

$$Reb\_flow_{j,t} = W_t - W_{t-1}(1 + r_{j,t}) = W_{j,t-1} r_{j,t}(\alpha_j - 1). \qquad (11)$$

As can be seen in Figure 10, rebalance-motivated trades can only account for a small fraction of the trading pattern we observe. For the ultra-wealthy group, their actual flows into (out of) the stock market in the early stage of the bubble (crash) are much larger than what can be explained by rebalancing motives. The two curves then run parallel to each other in the late stage of both the bubble and crash episodes. For the bottom two groups of households in terms of total account value, most of their trading in the first half of the bubble period can be explained by rebalancing motives. Figure 11 shows the gains and losses resulting from rebalance-motivated trades. Over our entire sample period, rebalancing-motivated trades, at the market level, can account for less than 20% of the 100B RMB transfer from the poor to the ultra-wealthy discussed in Section 4.

5.2. Variation in Risk Aversion

For the rest of the section, our benchmark case is the one in which capital flows into (or out of) stocks by each investor group are proportional to the group's initial capital share in the stock market. As described earlier, we view this part of the flow the "benchmark flow."[15] We then focus on investors' gains and losses stemming from the residual part of the trading that is unaccounted for by the initial wealth share, labelled the "adjusted flow." In other words, adjusted-flow generated gains and losses reflect investors' *idiosyncratic variation* in expectations and risk preferences.

In order for heterogeneous risk aversion to explain our results, we need the risk aversion of the ultra-wealthy to *decrease* relative to the poor during the boom period—so that they buy risky assets from the poor in the boom; we then need the risk aversion of the ultra-wealthy to *increase* relative to the poor during the bust period—so that the former sell risky assets to the latter. While this particular pattern of time-varying risk aversion is not entirely implausible, we do not see strong reasons to believe that risk aversion of these two groups should (or indeed) vary in this fashion during the boom-bust cycle. A similar argument can be made for the total financial wealth of various investor groups.

5.3. Variation in Expected Returns

Another potential explanation is that investors' subjective expected returns vary over time. In particular, in order to account for our results, we need the ultrawealthy to become

[15] This of course is a partial equilibrium statement, as this requires investors' expected returns, the difference between the expected payoffs and current price, to not depend on investor demand.

more bullish on the market, relative to the poor, in the boom period, and then to become more bearish in the bust period.

5.3.1. Simple Trend-Chasing Strategies

One possibility to generate this particular pattern in subjective expectations of future market returns is that the ultrawealthy follow a simple trend-chasing strategy, which happens to perform well in our sample period. To examine this channel, we run a kitchen-sink time-series regression of weekly capital flows by the wealthiest group, as well as the other four household groups, on lagged market returns at various horizons: over the past one, two, three, four weeks, as well as returns in the past two-to-six months and seven-to-twelve months. For ease of interpretation, we scale the dependent variable—weekly market-level capital flows of each household group—by the group's average portfolio value at the beginning and end of the same week.

To allow for variation in the boom and bust periods, we conduct separate regressions for the two subsamples. As can be seen from Table 3, most of the coefficients on past market returns are statistically insignificant; in other words, there is no clear pattern of trend chasing by either the wealthy or the poor in the boom or bust.

5.3.2. Market Timing

Our empirical results thus far are generally consistent with the view that the ultra-wealthy have superior market timing ability; that is, their subjective expectations are better aligned with future realized market returns than those of their peers. In particular, we show in Section 4 that at the market level (ignoring heterogeneity in portfolio compositions), the ultrawealthy outperform the relatively poor by over 100B RMB in this 18-month period, solely due to their ability to better time their capital flows into and out of the stock market.

While it is generally difficult to identify market timing ability in the time series (especially given our short sample period), market timing can also manifest itself in heterogeneity in portfolio choice – for example, by tilting portfolios toward high-beta stocks early in the boom period and low-beta stocks in the bust. To test this possibility, we analyze the relation between capital flows from the ultrawealthy, as well as from the relatively poor, with various stock characteristics.

To this end, we conduct Fama-MacBeth regressions of weekly capital flows to individual stocks by different household groups on market beta, and a battery of other stock characteristics, including the book-to-market ratio, past returns from various horizons (over the past one, two, three, and four weeks, as well as two-to-six and seven-to-twelve months), and a dummy variable indicating if a stock is in the marginable list.[16] Just like in Section 5.2.1, the dependent variable—i.e., stock-level capital flows of each household group—is normalized by the group's average portfolio value at the beginning and end of the same week (in basis points). We use unadjusted flows in these cross-sectional regressions to avoid the add-up constraint – since adjusted flows always sum up to zero, the coefficients across different household groups are mechanically linked.

[16] The marginable dummy is equal to one if the stock is in the marginable-stock list, and zero otherwise. The list of marginable stocks is determined by the China Securities Regulatory Commission based on a set of stock characteristics. For more details on margin trading in China, we refer the reader to Bian, Da, Lou, and Zhou (2018).

The results are shown in Table 4. Panel A presents results for the boom period and Panel B the bust period. As can be seen from Panel A, the coefficient on beta increases monotonically from the smallest household group to the wealthiest group: the coefficient ranges from -0.041 (t-statistic = -2.24) to 0.034 (t-statistic = 3.27). In other words, the wealthier groups tilt more towards high-beta stocks, while the smaller groups move away from high-beta firms in the boom period. Interestingly, as shown in Panel B, the relation completely reverses in the bust period: the wealthier groups now reduce their market exposures by moving out of high-beta stocks, while the smaller groups increase their holdings in high-beta stocks.

Figure 12 shows the time variation in portfolio betas of various household groups in our sample. To avoid the look-ahead bias, stock betas are calculated using monthly returns in the three years prior to July 2014 and are kept constant throughout the entire sample. The portfolio beta is then calculated as the value-weighted average holdings' beta. Moreover, to make the portfolio beta comparable across time, in each week, we subtract from each group's portfolio beta the capital-weighted average beta of the entire household sector. As can be seen from the figure, the wealthiest group (with the lowest portfolio beta to begin with) start increasing their market exposures early in the boom period, and start to aggressively reduce their market exposures shortly after the market peak. All the other four household groups exhibit the opposite trading behavior.

5.3.3. Stock Selection

Besides market-timing ability, our evidence also suggests that wealthier investors are more skilled at stock selection than their peers. For example, as shown in Section 4, accounting for heterogeneity in portfolio choice more than doubles the magnitude of wealth transfer between the poor and wealthy, compared to when we only consider gains and losses at the market level. To formally examine investors' stock selection skills, we conduct Fama-MacBeth forecasting regressions of future stock returns on stock-specific capital flows by the five household groups.

Before showing the results from these return regressions, we wish to highlight a few additional observations from Table 4—the relation between stock-level flows by household groups and firm characteristics. First, during the boom period, wealthy households are net buyers of large-cap, value, and marginable stocks while poor households are net sellers in all three; the differences in coefficients between groups one and five are highly statistically significant. During the bust period, interestingly, households with different wealth levels have similar tendencies to sell large cap, value, marginable stocks. Second, throughout our entire sample, the wealthiest households bet against short-term past stock returns, while all the other four groups chase short-term stock returns. Since the short-term contrarian strategy performs well in our sample period, this partly explains why the wealthy outperform the poor.

Panels A and B of Table 5 report results from univariate return regressions, with normalized capital flows from various household groups being the only explanatory variable. As is clear from the two panels, capital flows by the three smallest investor groups are significantly and negatively associated with future stock returns in the next one to four weeks. Capital flows of the ultrawealthy, on the other hand, significantly and positively forecast future stock returns in the next one to four weeks. These return patterns further corroborate the view that the ultrawealthy, relative to the poor, have superior stock selection ability.

Panels C and D further control for the same set of stock characteristics as in Table 4. The results shown in these two panels suggest that households' differential responses to these stock characteristics (as shown in Table 4) are unlikely to be driving the observed differences in their portfolio returns. Across all specifications, the coefficient estimate on *Flow* is at most 20% smaller in Panels C and D compared to the corresponding estimate in Panels A and B. In other words, the ultrawealthy have better access to stock-specific information not captured by observable firm characteristics.

Table 6 repeats the same exercise in Table 5 for two subperiods: pre- and post-October 2014 (calm vs. extreme market conditions). As shown in Panels A and B, the return predictability of trades (per standard deviation of change in flows) by various household groups in the post-October 2014 period is two to three times as large as that in the pre-October 2014 period. In Panels C and D, we further include the same set of stock characteristics as in Tables 4 and 5 on the right hand side of the regression equation, and the results are virtually unchanged. These results are consistent with the view that the information advantage of the ultra-wealthy is amplified in periods with extreme market movements/volatilities.

Finally, our documented return pattern is unlikely to be driven by flow-induced price pressure; untabulated results show that over longer horizons, the relation between capital flows by various household groups and the cross-section of average stock returns becomes statistically insignificant but does not revert. (All results described here hold similarly for adjusted flows.)

6. Conclusion

In this paper, we take the perspectives of ordinary people—investors, pensioners, savers—and examine a novel aspect of the social impact of financial markets: the wealth redistribution role of financial bubbles and crashes. Our setting is the Chinese stock market between July 2014 and December 2015, during which the market index rose more than 150% before crashing 40%. Our regulatory bookkeeping data include daily holdings and transactions of all individual accounts in the Shanghai Stock Exchange, thus enabling us to examine wealth transfers across the entire investing population.

Our results reveal that wealthy investors, those in the top 0.1% of the wealth distribution, actively increase their market exposures—through both inflows into the stock market and tilting towards high beta stocks—in the early stage of the bubble period. They then quickly reduce their market exposures shortly after the market peak. Relatively poor investors (those below the 90th percentile in the wealth distribution) exhibit the exact opposite trading behavior. Consequently, there is a net transfer of over 200B RMB from the poor to the super wealthy over this 18-month period, which amounts to nearly 30% of their initial account value. Using a stylized model of portfolio choice, we show that this wealth transfer is mostly a reflection of differences in investment skills.

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Figure 1. Anatomy of Flows: Cumulative Flows by Investor Sectors

This figure plots cumulative capital flows by different investor sectors—households, institutions, and corporations—as well as the sum of their flows, which is equal to the total increase of tradable shares in the market, from July 2014 to December 2015. The flows are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

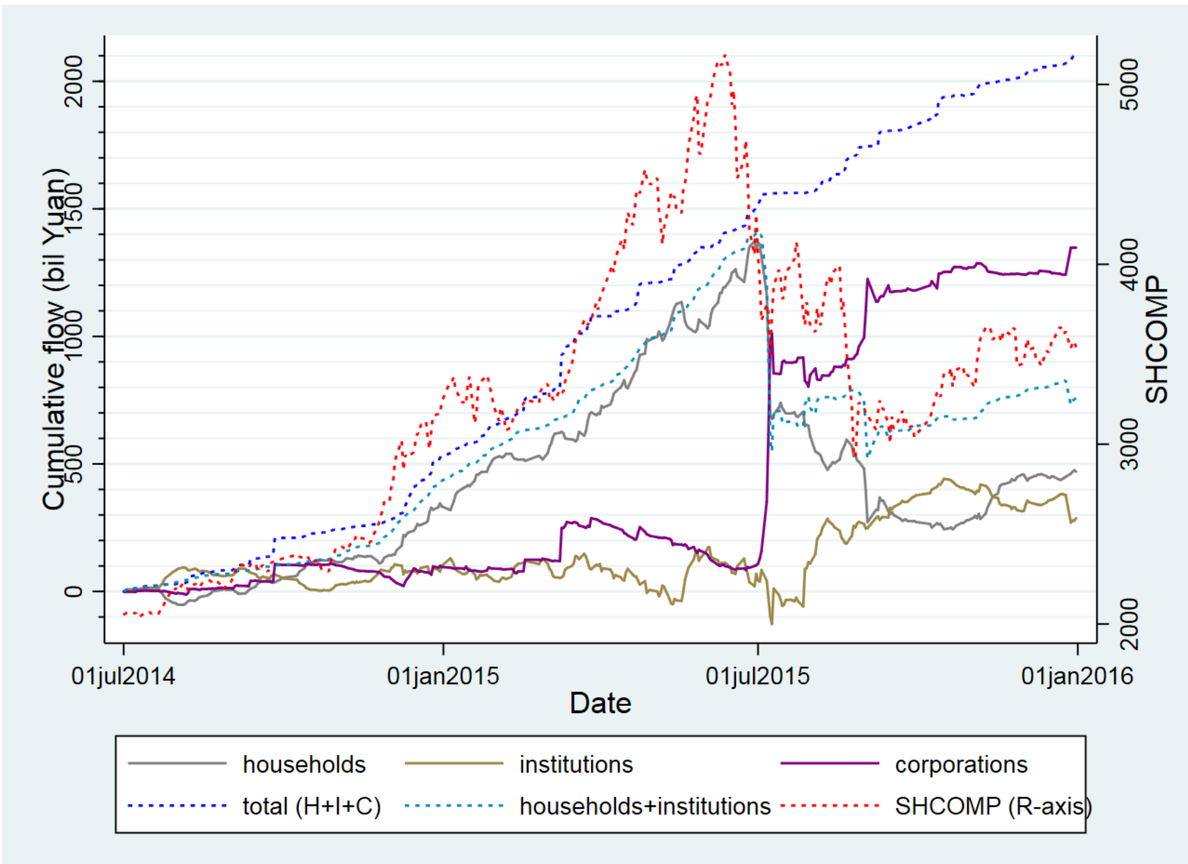

Figure 2. Cumulative Flows of the Household Sector: by Wealth Groups

This figure plots cumulative capital flows by investor groups in the household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. The flows are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

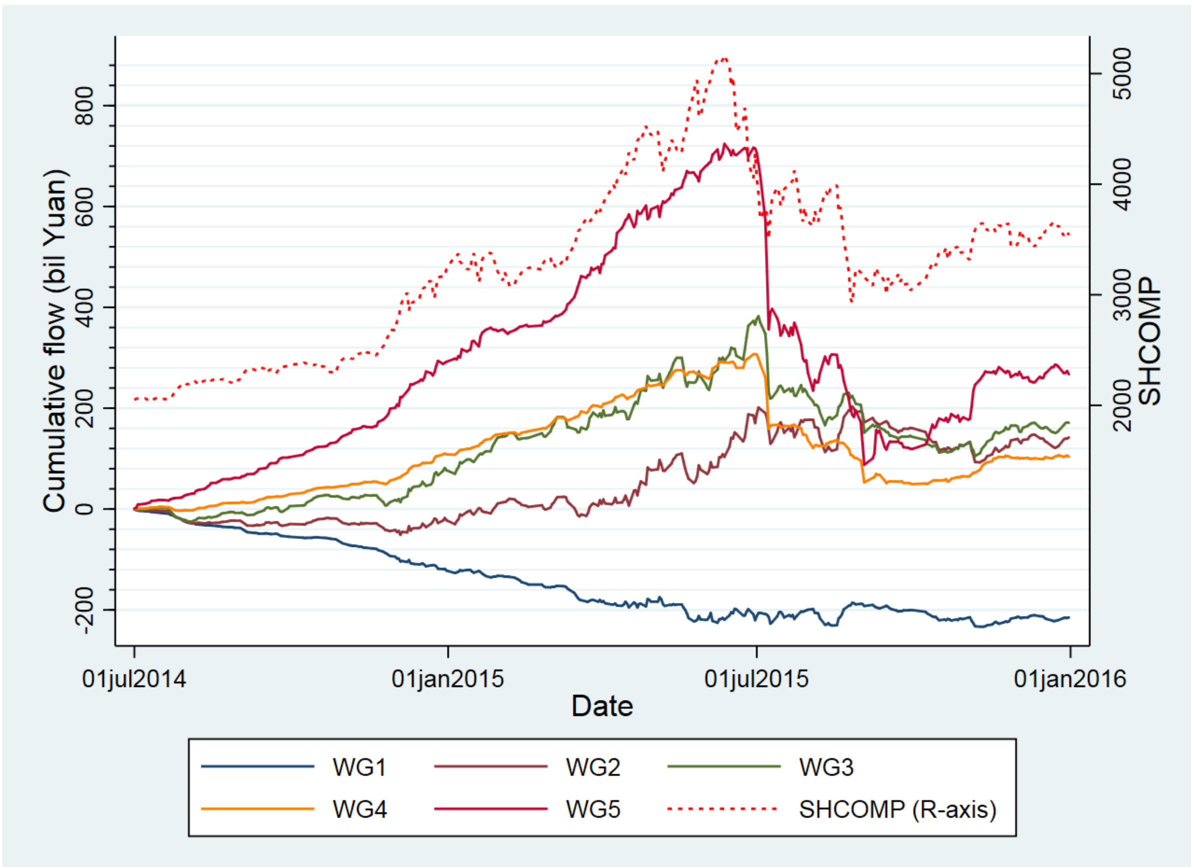

Figure 3. Cumulative Adjusted Flows of the Household Sector: by Wealth Groups

This figure plots cumulative adjusted capital flows by investor groups in the household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. We adjust the raw value of flow for each group in each day by subtracting a fixed fraction of the capital flow of the entire household sector, where the fraction is equal to the capital weight of that group at the beginning of the sample (see Eq (3)). The flows are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

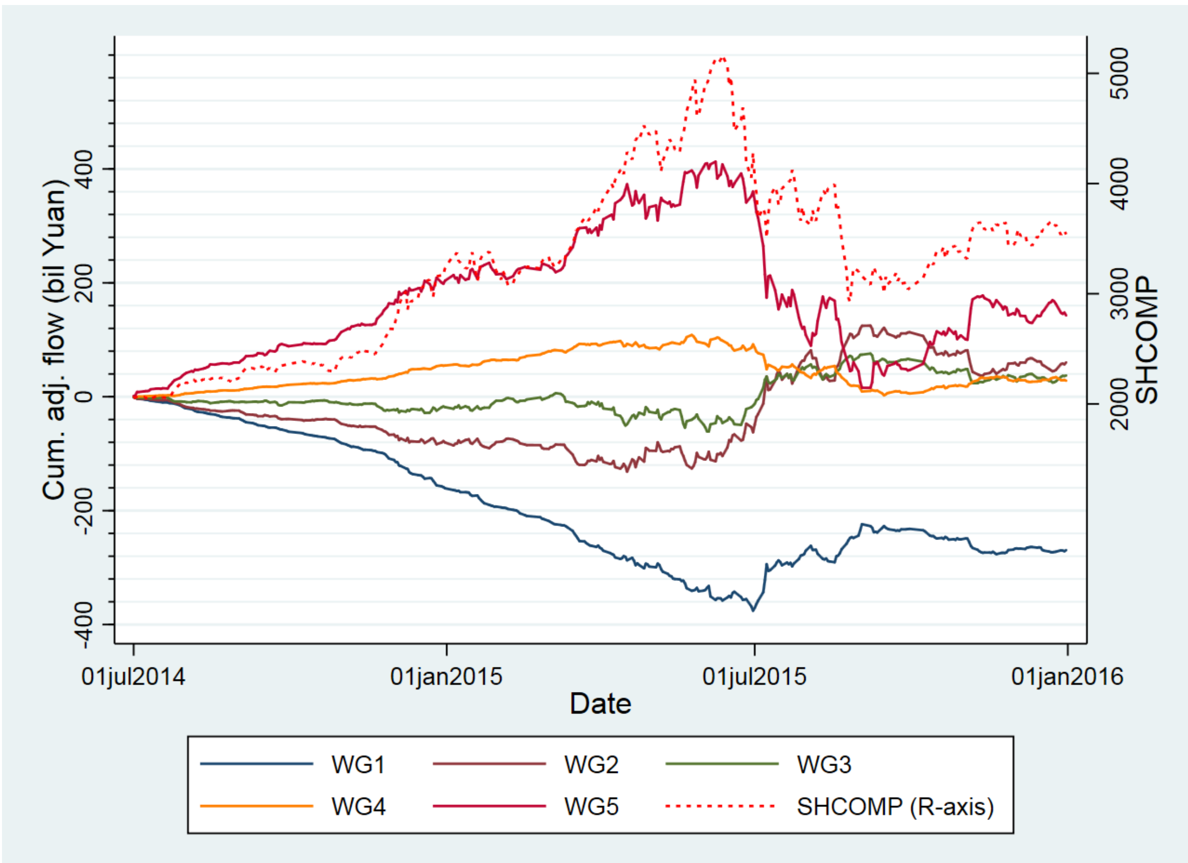

Figure 4. Flow-Generated Gains at the Market Level: by Investor Sectors

This figure plots cumulative flow-generated gains at the market level by different investor sectors—households, institutions, and corporations—from July 2014 to December 2015. Focusing on the gains and losses generated by variation in market timing of different groups, we assume every RMB invested the market is tracking the market index. The flow-generated gains are calculated by interacting daily flows with subsequent market returns (see Eq (4)). The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

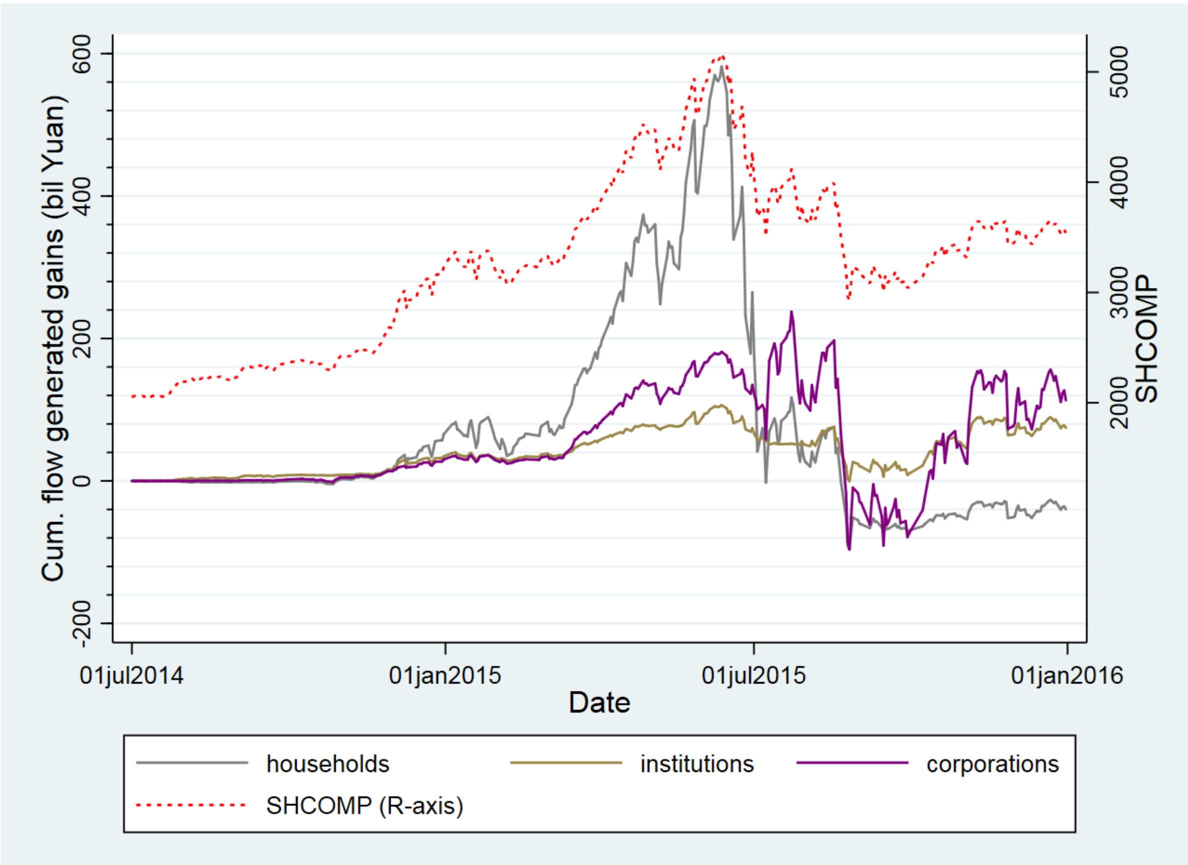

Figure 5. Flow-Generated Gains at the Market Level for the Household Sector: by Wealth Groups

This figure plots cumulative flow-generated gains at the market level by investor groups in the household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. Focusing on the gains and losses generated by variation in market timing of different groups, we assume every RMB invested the market is tracking the market index. The flow-generated gains are calculated by interacting daily flows with subsequent market returns (see Eq (4)). The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

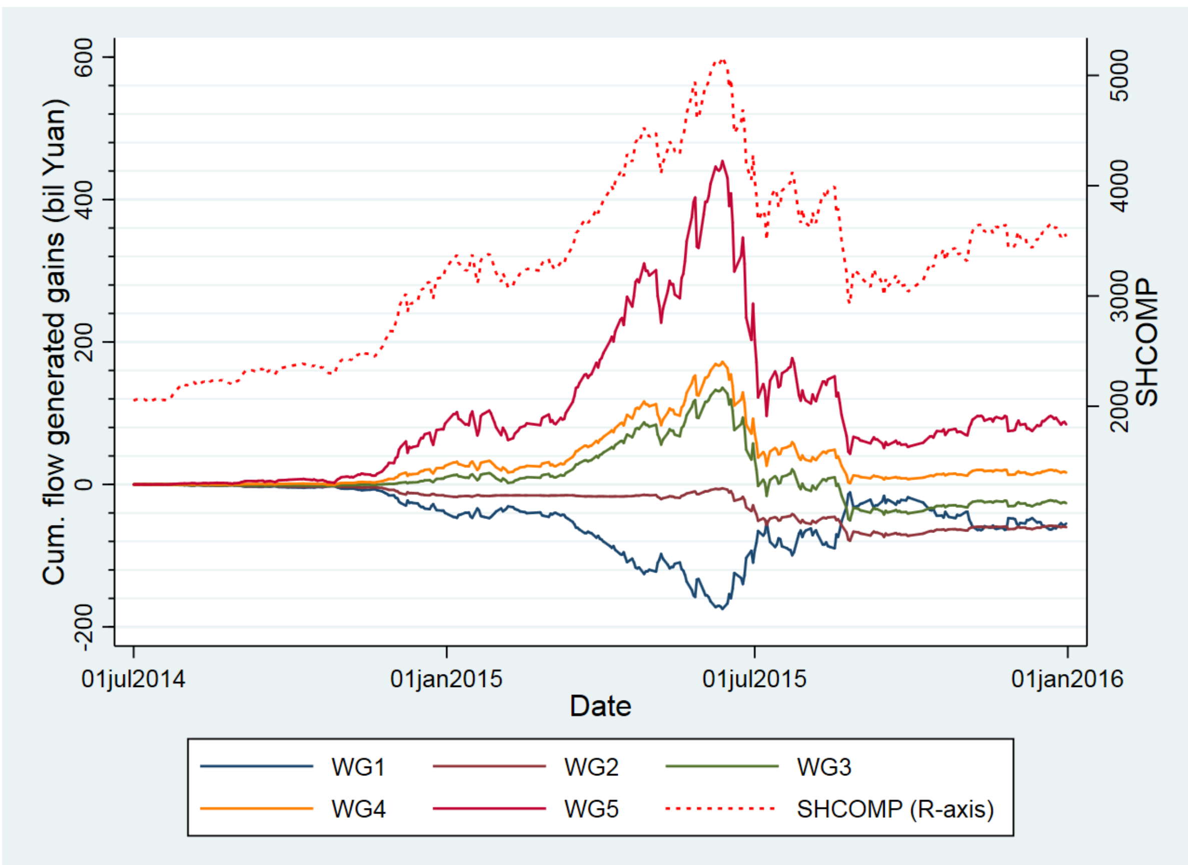

Figure 6. Adjusted-Flow-Generated Gains at the Market Level for the Household Sector: by Wealth Groups

This figure plots cumulative adjusted-flow-generated gains at the market level by investor groups in the household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. Focusing on the gains and losses generated by variation in market timing of different groups, we assume every RMB invested the market is tracking the market index. The adjusted-flow-generated gains are calculated by interacting daily adjusted flows with subsequent market returns (see Eq (5)). The adjustment for flow is calculated according to Eq (3). The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

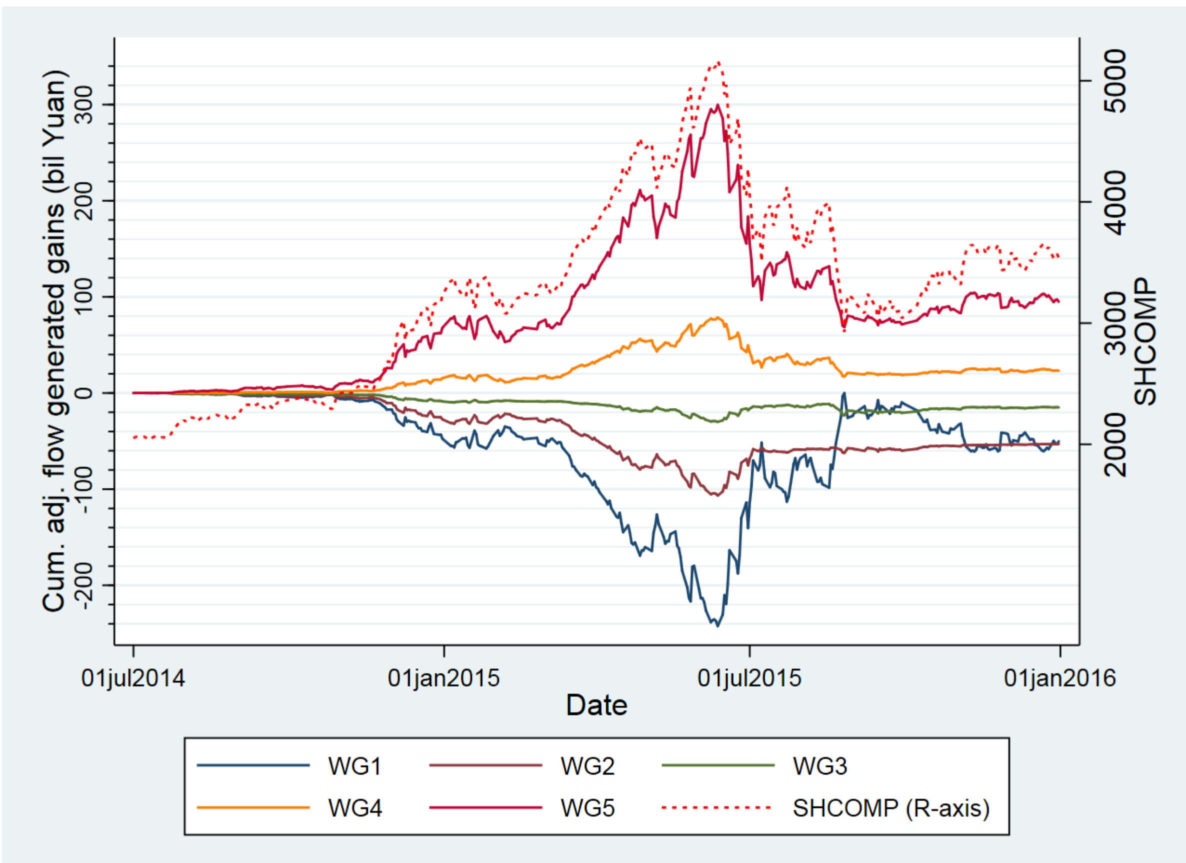

Figure 7. Flow-Generated Gains at the Stock Level: by Investor Sectors

This figure plots cumulative flow-generated gains at the stock level by different investor sectors—households, institutions, and corporations—from July 2014 to December 2015. Taking into account the effects of both market timing and portfolio choice, we calculate the flow-generated gains at the stock level by interacting daily flows with subsequent returns of the stocks that investors actually trade (see Eq (7)). The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

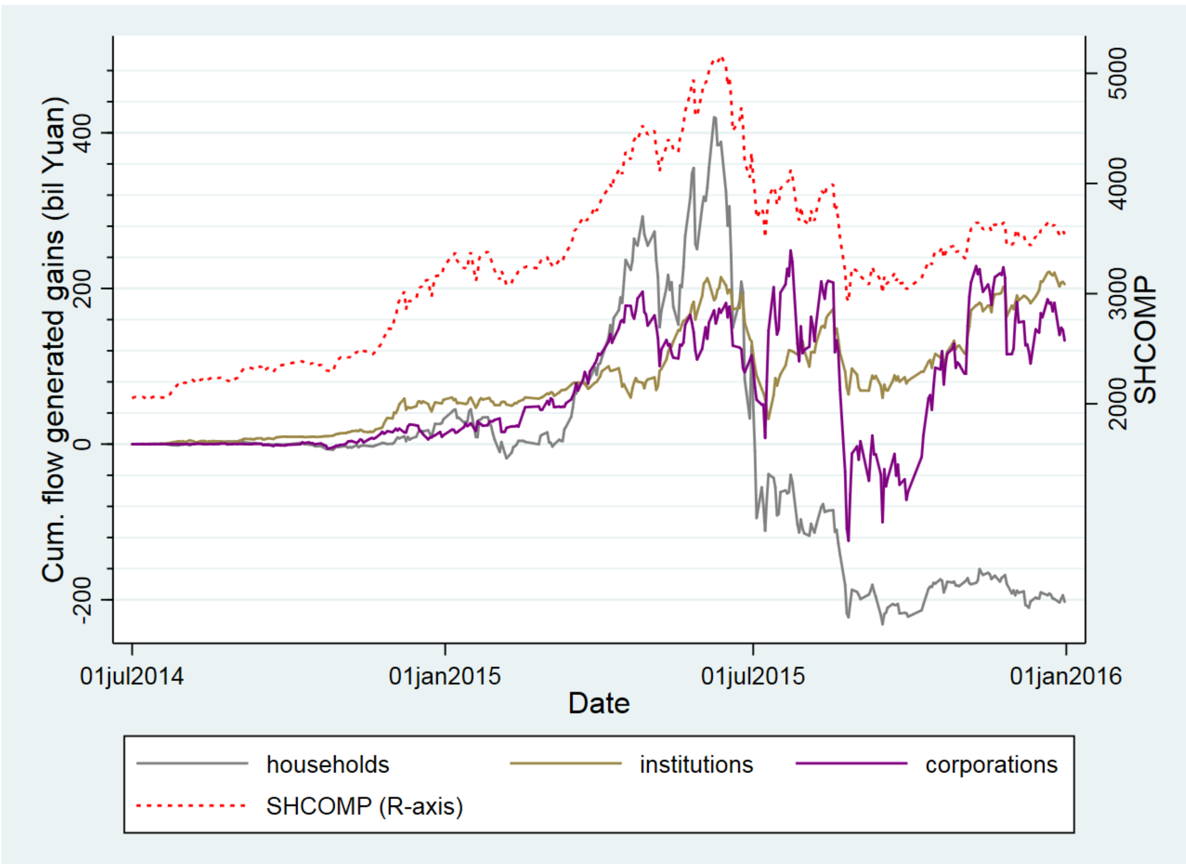

Figure 8. Flow-Generated Gains at the Stock Level for the Household Sectors: by Wealth Groups

This figure plots cumulative flow-generated gains at the stock level by investor groups in the household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. Taking into account the effects of both market timing and portfolio choice, we calculate the flow-generated gains at the stock level by interacting daily flows with subsequent returns of the stocks that investors actually trade (see Eq (7)). The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

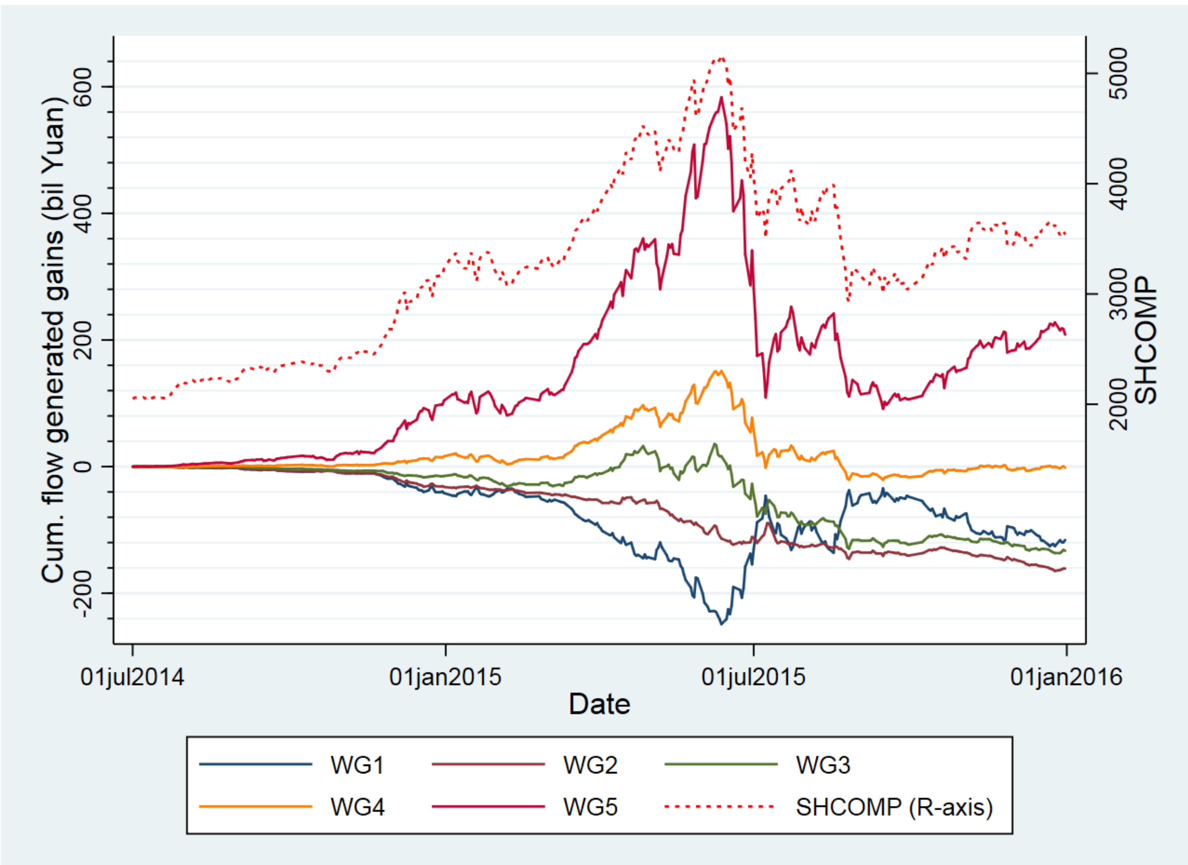

Figure 9. Adjusted-Flow-Generated Gains at the Stock Level for the Household Sectors: by Wealth Groups

This figure plots cumulative asjusted-flow-generated gains at the stock level by investor groups in the household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. Taking into account the effects of both market timing and portfolio choice, we calculate the adjusted-flow-generated gains at the stock level by interacting daily adjusted flows with subsequent returns of the stocks that investors actually trade (see Eq (8)). The adjustment for flow is calculated according to Eq (6). The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

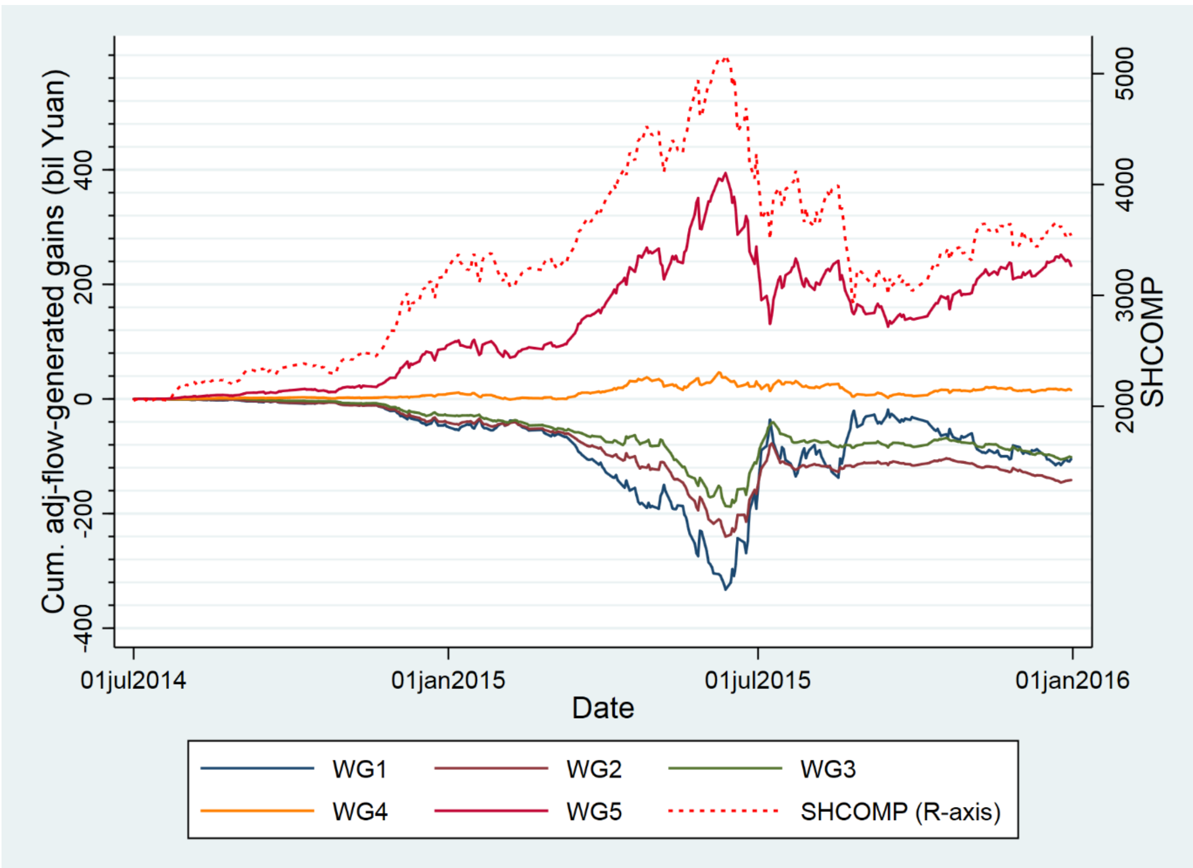

Figure 10. Cumulative Rebalance-Motivated Capital Flows of the Household Sector: by Wealth Groups

This figure plots hypothetical rebalance-motivated capital flows (in dotted lines), as well as the actual cumulative flows (in solid lines), of the wealthiest and the bottom two household groups from July 2014 to December 2015. hypothetical rebalance-motivated capital flows are calculated according to Eq (10) and (11). WG1 and WG2 include investors with account value less than 500K, while WG5 indicates investors holding account value greater than 10M. The flows are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

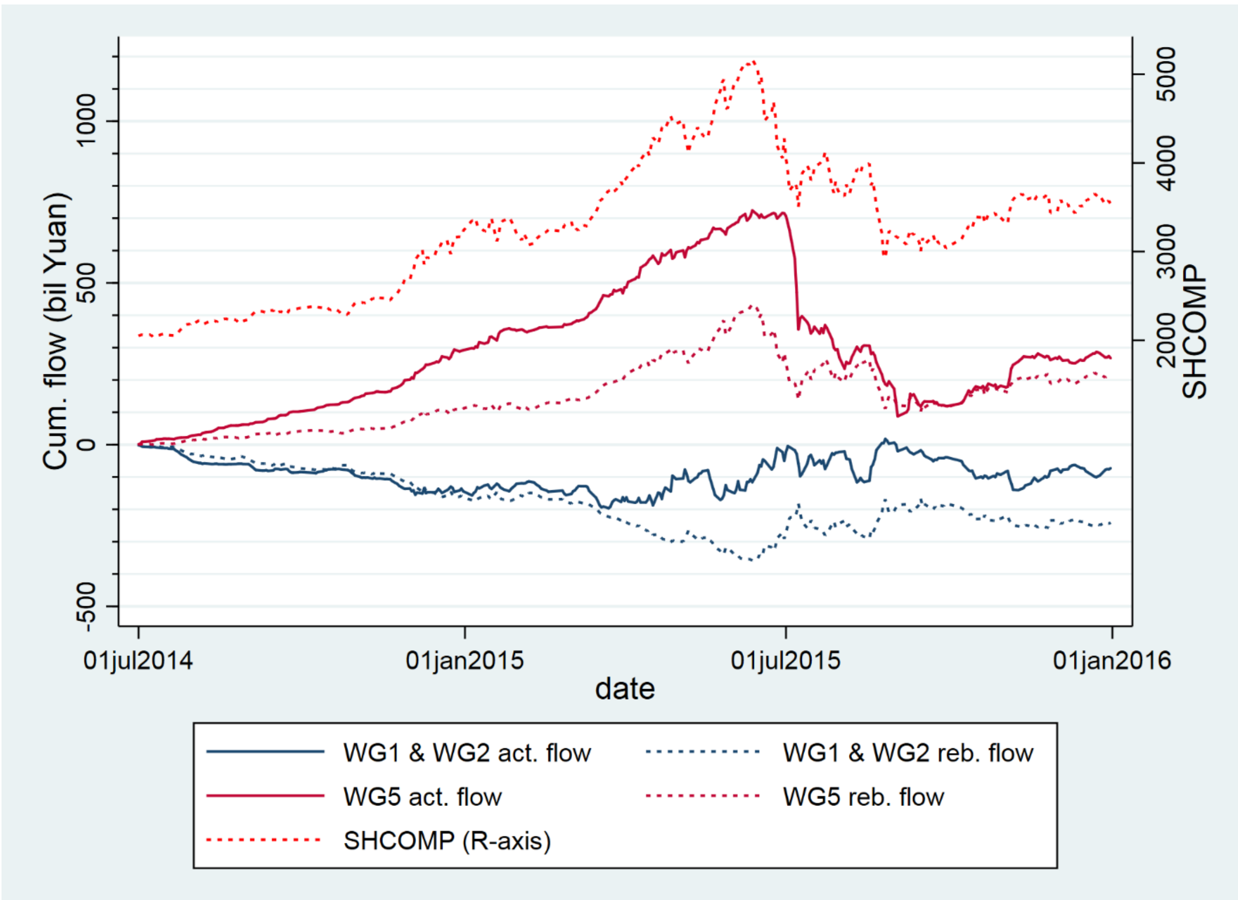

Figure 11. Rebalance-Motivated-Flow-Generated Gains of the Household Sector: by Wealth Groups

This figure plots hypothetical rebalance-motivated-flow-generated gains at the market level (in dotted lines), as well as the actual flow-generated gains at the market level (in solid lines), of the wealthiest and the bottom two household groups from July 2014 to December 2015. Hypothetical rebalance-motivated flows are calculated according to Eq (10) and (11). WG1 and WG2 include investors with account value less than 500K, while WG5 indicates investors holding account value greater than 10M. The capital gains are in the unit of billion RMB, and are plotted against the left y-axis. Shanghai Composite Index is plotted against the right y-axis.

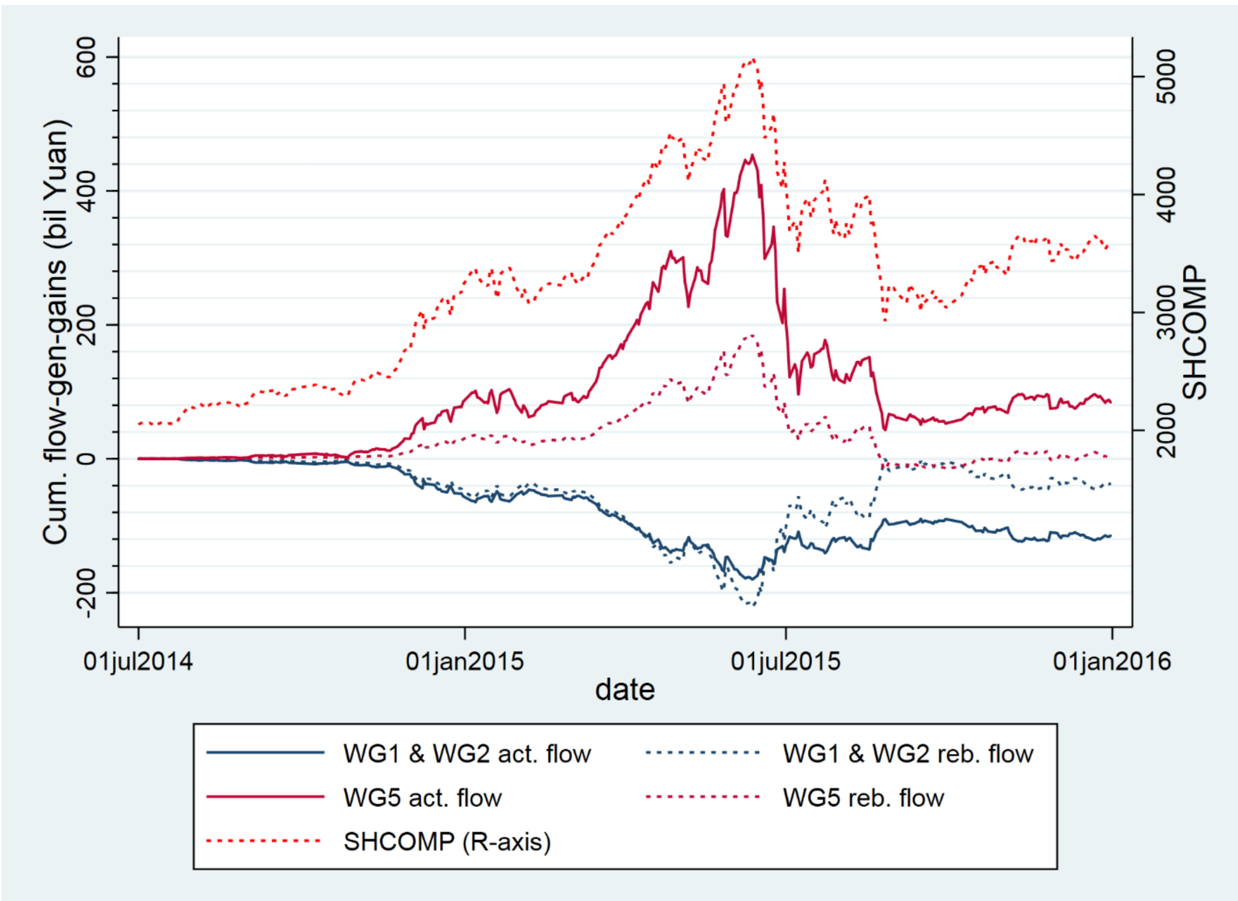

Figure 12. Portfolio Betas of the Household Sector: by Wealth Groups

This figure plots average portfolio beta by investor groups in the household sector from July 2014 to December 2015. Stock-level betas are estimated using 36 months of returns prior to July 2014 and are kept constant throughout the sample. Portfolio betas are calculated by value weighting using the holdings of the investor group as of the time point, and then adjusted by subtracting the capital-weighted portfolio beta of the entire household sector. All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M.

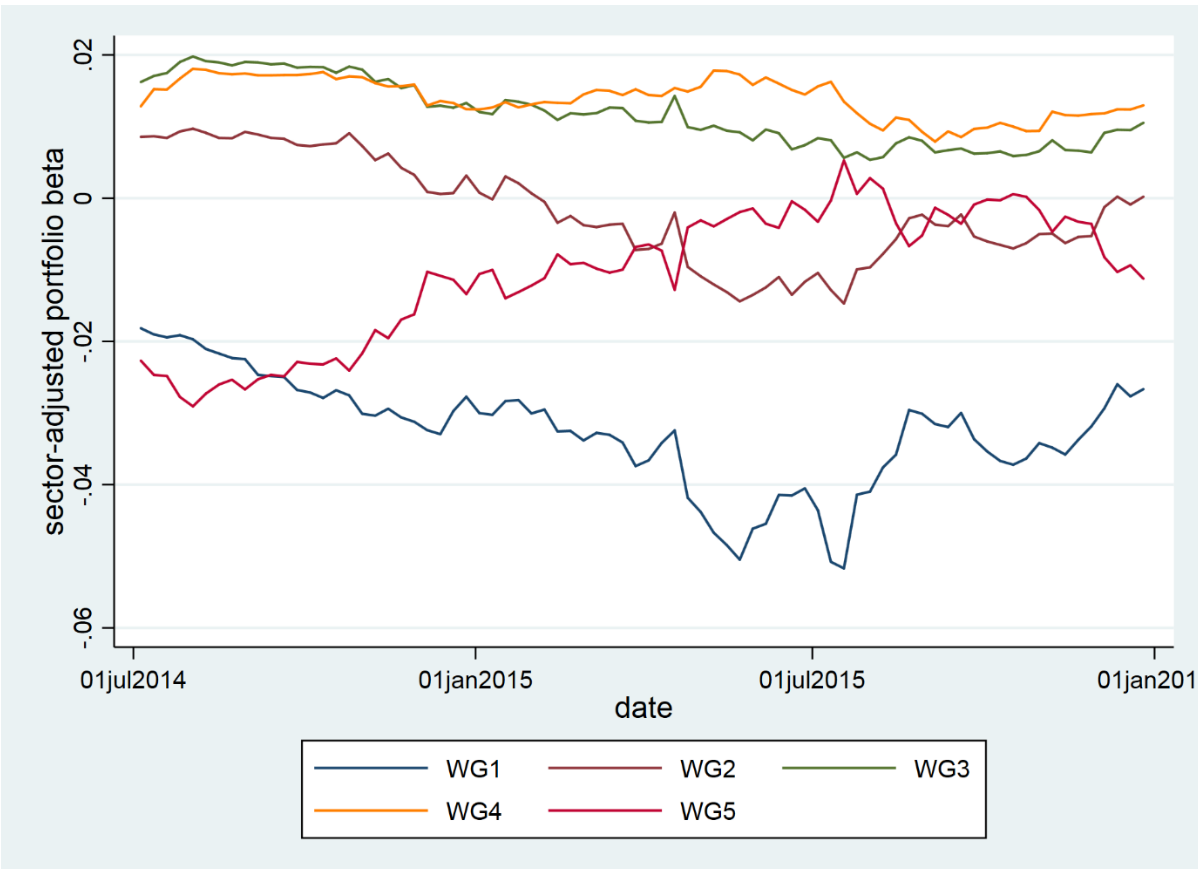

Table 1. Account Value and Trading Volume by Different Investor Groups

This table reports summary statistics for account value and trading volume by different investor groups. The entire investing population is classified into three broad catergories: households, institutions, and corporations. Within the household sector, investors are further classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. Account value and trading volume are in the unit of billion RMB. Initial account value and capital share are calculated on July 1st, 2014.

	HHs	Inst	Corps	WG1	WG2	WG3	WG4	WG5
average account value (B)	5303	2417	13736	369	852	1505	915	1664
initial account value (B)	2901	1461	8733	335	504	828	467	767
average capital share	24.3%	11.3%	64.4%	1.8%	3.9%	6.9%	4.2%	7.5%
initial capital share	22.2%	11.2%	66.7%	2.6%	3.8%	6.3%	3.6%	5.9%
average daily volume (B)	376	50	8	25	66	115	69	100
average volume share	86.6%	11.7%	1.7%	6.2%	14.9%	26.6%	15.9%	23.0%

Table 2. Summary of Capital Flows and Flow-Generated Gains for Different Groups of Retail Investors in Different Periods

This table summarizes the figures of capital flows (Panel A), flow-generated gains (Panel B and C), and the initial account value (Panel D) for the five household groups in different periods. Figures in Panel A and B correspond to the values in Figures 2, 3, 5, 6, 8, and 9. Panel C reports flow-generated gains in different stock groups sorted by return volatilities (controlling for firm size). All retail investors are classified into five groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash), with cutoffs at RMB 100K, 500K, 3M, and 10M. WG1 indicates investors with account value less than 100K, while WG5 indicates investors holding account value greater than 10M. All numbers are in the unit of billion RMB.

	WG1	WG2	WG3	WG4	WG5
Panel A. Capital flows					
mild increase (140701-141024)					
flow into the market	-57	-18	28	43	124
adjusted flow into the market	-73	-40	-9	23	98
boom period (140701-150612)					
flow into the market	-219	103	294	291	724
adjusted flow into the market	-358	-104	-46	99	408
bust period (150612-151231)					
flow into the market	5	39	-123	-187	-457
adjusted flow into the market	88	164	83	-70	-265
the entire period (140701-151231)					
flow into the market	-215	142	171	104	267
adjusted flow into the market	-269	60	37	28	143

Panel B. Flow-generated gains					
the entire period (140701-151231)					
Flow-gen gains at the market level	-55	-60	-26	17	84
Adj-flow-gen gains at the market level	-50	-53	-15	23	95
Flow-gen gains at the stock level	-116	-161	-133	-2	209
Adj-flow-gen gains at the stock level	-105	-141	-101	16	232
relatively calm period (140701-141024)					
Flow-gen gains at the market level	-2	-2	-2	0	3
Adj-flow-gen gains at the market level	-2	-2	-1	0	4
Flow-gen gains at the stock level	-5	-7	-5	0	11
Adj-flow-gen gains at the stock level	-5	-6	-4	1	12

	WG1	WG2	WG3	WG4	WG5
Panel C. Flow-generated gains in stock groups sorted by return volatilities (size-adjusted)					
stocks with lowest vol					
flow-gen gains	-11	-13	-11	-2	10
adj-flow-gen gains	-8	-9	-4	1	14
stocks in 2nd quintile					
flow-gen gains	-13	-13	-10	0	10
adj-flow-gen gains	-9	-7	-1	4	15
stocks in 3rd quintile					
flow-gen gains	-16	-19	-10	4	35
adj-flow-gen gains	-14	-14	-3	8	39
stocks in 4th quintile					
flow-gen gains	-20	-24	-16	4	43
adj-flow-gen gains	-17	-19	-9	8	49
stocks with highest vol					
flow-gen gains	-45	-73	-66	-5	92
adj-flow-gen gains	-45	-72	-63	-3	95

Panel D. Account values					
initial account value (at 140701)	335	504	828	467	767

Table 3. Market-Level Flow Sensitivity

This table shows results by regressing market-level capital flows of different investor groups in the next week onto past market returns at different horizons (over the past one, two, three, four weeks, as well as 2-to-6 months and 7-to-12 months). Flow for one investor group is calculated as the capital flow at the market level in a given week, normalized by the average portfolio value of that investor group at the beginning and at the end of the week. WG1 to WG5 indicates investor groups classified by their account values, in the brackets of <100K, 100-500K, 500K-3M, 3M-10M, and >10M, respectively. Panel A shows the results for the boom period, and Panel B presents the results for the bust period. All regressions are at weekly level, and t-statisitcs, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags.

Panel A. Boom period (140701-150612)					
	(1)	(2)	(3)	(4)	(5)
	Weekly flows at the market level				
	WG1	WG2	WG3	WG4	WG5
$Mret_{-1w}$	0.170**	0.176***	0.084**	0.037	0.006
	[2.19]	[2.71]	[2.05]	[1.28]	[0.22]
$Mret_{-2w}$	0.039	0.059	0.034	0.048*	0.063***
	[1.06]	[1.19]	[0.99]	[1.83]	[2.76]
$Mret_{-3w}$	0.004	0.024	0.012	-0.006	-0.002
	[0.08]	[0.37]	[0.22]	[-0.16]	[-0.07]
$Mret_{-4w}$	-0.051	0.017	0.031	0.015	-0.007
	[-0.73]	[0.25]	[0.69]	[0.57]	[-0.23]
$Mret_{-2m, -6m}$	0.002	0.015*	0.009	0.006*	-0.005
	[0.20]	[1.83]	[1.53]	[1.70]	[-0.81]
$Mret_{-7m, -12m}$	0.006	-0.007	-0.015	-0.019**	-0.001
	[0.19]	[-0.35]	[-1.22]	[-2.05]	[-0.05]
Constant	-0.015***	-0.007***	-0.001	0.004**	0.010***
	[-5.76]	[-3.15]	[-0.54]	[2.44]	[5.86]
No. Obs.	49	49	49	49	49

Panel B. Bust period (150612-151231)					
	(1)	(2)	(3)	(4)	(5)
	Weekly flows at the market level				
	WG1	WG2	WG3	WG4	WG5
$Mret_{-1w}$	0.192**	0.159**	0.096**	0.066	0.045
	[2.74]	[2.77]	[2.44]	[1.42]	[0.66]
$Mret_{-2w}$	0.019	0.080	0.073	0.054	0.026
	[0.18]	[0.65]	[0.52]	[0.32]	[0.13]
$Mret_{-3w}$	-0.096	-0.034	-0.013	0.004	0.051
	[-0.88]	[-0.36]	[-0.17]	[0.06]	[0.67]
$Mret_{-4w}$	0.074	0.073	0.031	-0.007	-0.045
	[0.99]	[1.16]	[0.45]	[-0.07]	[-0.34]
$Mret_{-2m, -6m}$	0.011	0.010	-0.013	-0.032**	-0.056***
	[0.69]	[0.78]	[-1.31]	[-2.56]	[-2.90]
$Mret_{-7m, -12m}$	-0.025	-0.030	-0.019	-0.003	-0.013
	[-0.70]	[-1.15]	[-0.96]	[-0.11]	[-0.33]
Constant	0.015	0.019	0.010	-0.002	0.003
	[0.64]	[1.14]	[0.80]	[-0.12]	[0.13]
No. Obs.	29	29	29	29	29

Table 4. Stock-Level Flow Sensitivity

This table shows Fama-MacBeth estimations by regressing stock-level capital flows of different investor groups in the next week onto a battery of stock characteristics, including beta, firm size (size), book-to-market ratio (bm), a dummy variable indicating whether a stock is marginable (margin), and past returns at different horizons (over the past one, two, three, four weeks, as well as 2-to-6 months and 7-to-12 months). Flow for one investor group is calculated as the capital flow at stock level in a given week, normalized by the average portfolio value of that investor group at the beginning and at the end of the week. Flow variables are in the unit of basis point (×10000). WG1 to WG5 indicates investor groups classified by their account values, in the brackets of $<$100K, 100-500K, 500K-3M, 3M-10M, and $>$10M, respectively. Panel A shows the results for the boom period, and Panel B presents the results for the bust period. T-statisitcs, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags.

Panel A. Boom period (140701-150612)					
	(1)	(2)	(3)	(4)	(5)
	Weekly flows × 10000				
	WG1	WG2	WG3	WG4	WG5
Beta	-0.041**	-0.055**	-0.029	-0.002	0.034***
	[-2.24]	[-2.49]	[-1.25]	[-0.12]	[3.27]
Size	-0.001	0.001	0.001***	0.001***	0.002**
	[-1.53]	[1.66]	[2.78]	[3.22]	[2.56]
BM	-0.114	-0.038	-0.016	0.028	0.116***
	[-1.45]	[-0.56]	[-0.37]	[0.90]	[3.06]
Margin	-0.090***	-0.006	0.015	0.045***	0.080***
	[-3.55]	[-0.23]	[0.87]	[3.02]	[4.31]
Ret_{-1w}	0.478	1.396***	0.829***	0.229	-1.482***
	[0.81]	[2.94]	[2.94]	[1.00]	[-6.46]
Ret_{-2w}	0.412	1.076***	0.748***	0.255	-0.464***
	[1.33]	[3.84]	[3.65]	[1.45]	[-3.54]
Ret_{-3w}	0.334***	0.953***	0.651***	0.279**	-0.282
	[2.70]	[5.20]	[4.31]	[2.03]	[-1.27]
Ret_{-4w}	0.394**	0.979***	0.670***	0.247*	-0.373***
	[2.45]	[5.52]	[4.45]	[1.90]	[-2.75]
$Ret_{-2m, -6m}$	0.054	0.224***	0.141***	0.046**	-0.086***
	[1.24]	[6.03]	[5.40]	[2.05]	[-3.85]
$Ret_{-7m, -12m}$	0.017	0.093***	0.067***	0.040**	-0.006
	[0.50]	[2.78]	[3.09]	[2.57]	[-0.26]
Constant	-0.093	-0.112	-0.051	-0.005	0.032
	[-1.31]	[-1.56]	[-1.04]	[-0.14]	[0.76]
No. Obs.	41,086	41,086	41,086	41,086	41,086
Adj-R^2	0.098	0.130	0.111	0.080	0.067
No. Weeks	49	49	49	49	49

Panel B. Bust period (150612-151231)					
	(1)	(2)	(3)	(4)	(5)
	Weekly flows × 10000				
	WG1	WG2	WG3	WG4	WG5
Beta	0.066**	0.050*	0.018	-0.008	-0.029
	[2.32]	[1.75]	[1.04]	[-0.62]	[-1.25]
Size	-0.001	-0.001*	-0.001*	-0.001*	-0.002*
	[-1.68]	[-1.75]	[-1.83]	[-1.86]	[-1.76]
BM	-0.100	-0.113*	-0.135***	-0.151***	-0.228*
	[-1.37]	[-1.92]	[-2.78]	[-2.83]	[-1.72]
Margin	0.036	0.031	0.003	-0.031	-0.128
	[0.90]	[0.91]	[0.11]	[-0.68]	[-1.47]
Ret_{-1w}	1.653***	1.316***	0.683***	-0.100	-1.973***
	[3.85]	[4.29]	[3.23]	[-0.39]	[-4.80]
Ret_{-2w}	0.616**	0.618***	0.470***	0.208	-0.235
	[2.41]	[3.57]	[3.76]	[1.44]	[-0.67]
Ret_{-3w}	0.658***	0.619***	0.403***	0.151	-0.481***
	[4.77]	[6.40]	[4.78]	[1.70]	[-3.02]
Ret_{-4w}	0.404**	0.410***	0.353**	0.309**	-0.241
	[2.46]	[3.07]	[2.76]	[2.27]	[-1.67]
$Ret_{-2m, -6m}$	0.116	0.114**	0.080**	0.053	-0.121**
	[1.53]	[2.67]	[2.57]	[1.48]	[-2.73]
$Ret_{-7m, -12m}$	-0.048	-0.046	-0.061*	-0.070*	-0.079
	[-0.77]	[-1.02]	[-1.73]	[-1.89]	[-1.34]
Constant	-0.142**	-0.112**	-0.077**	-0.067	0.103
	[-2.22]	[-2.58]	[-2.24]	[-1.40]	[0.72]
No. Obs.	22,438	22,438	22,438	22,438	22,438
Adj-R^2	0.145	0.158	0.145	0.128	0.109
No. Weeks	29	29	29	29	29

Table 5. Return Predictability of Flows by Different Investor Groups

This table shows Fama-MacBeth estimations by regressing future returns on weekly stock-level capital flows of different investor groups. Panels A and B show the univariate results, and Panels C and D additionally control for a battery of stock characteristics, including beta, firm size (size), book-to-market ratio (bm), a dummy variable indicating whether a stock is marginable (margin), and past returns at different horizons (over the past one, two, three, four weeks, as well as 2-to-6 months and 7-to-12 months). The dependent variable is future 1-week return in Panels A and C, and it is future 4-week return in Panels B and D. Flow for one investor group is calculated as the capital flow at stock level in a given week, normalized by the average total asset holdings of that investor group at the beginning and at the end of the week. Flow variables are in the unit of basis point (×10000), and the return variables are in the unit of percentage point (×100). WG1 to WG5 indicates investor groups classified by their account values, in the brackets of <100K, 100-500K, 500K-3M, 3M-10M, and >10M, respectively. All regessions are run at stock-week level, and t-statisitcs, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags.

Panel A. Future 1-week return					
	(1)	(2)	(3)	(4)	(5)
	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.253***	-0.359***	-0.315***	-0.066	0.277***
	[-3.77]	[-5.71]	[-4.07]	[-0.70]	[6.77]
Constant	1.187	1.238	1.228	1.221	1.188
	[1.48]	[1.56]	[1.54]	[1.53]	[1.49]
No. Obs.	71,671	71,671	71,671	71,671	71,671
Adj-R^2	0.009	0.010	0.011	0.010	0.008
No. Weeks	78	78	78	78	78

Panel B. Future 4-week return					
	(1)	(2)	(3)	(4)	(5)
	$Ret_{1w,\ 4w}$				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.522***	-0.754***	-0.583**	-0.131	0.575***
	[-2.76]	[-3.50]	[-2.10]	[-0.52]	[5.49]
Constant	4.047	4.127	4.134	4.152	4.074
	[1.43]	[1.45]	[1.45]	[1.46]	[1.44]
No. Obs.	72,070	72,070	72,070	72,070	72,070
Adj-R^2	0.011	0.014	0.014	0.011	0.007
No. Weeks	78	78	78	78	78

Panel C. Future 1-week return					
	(1)	(2)	(3)	(4)	(5)
	Ret$_{1w}$				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.319***	-0.477***	-0.390***	-0.109	0.259***
	[-7.51]	[-7.63]	[-4.98]	[-1.22]	[6.53]
Beta	-0.111	-0.122	-0.116	-0.109	-0.111
	[-0.62]	[-0.68]	[-0.65]	[-0.60]	[-0.62]
Size	-0.001	-0.000	-0.000	-0.000	-0.001
	[-0.92]	[-0.60]	[-0.54]	[-0.37]	[-0.62]
BM	0.284	0.304	0.316	0.317	0.315
	[0.54]	[0.57]	[0.60]	[0.61]	[0.60]
Margin	-0.234	-0.214	-0.220	-0.217	-0.234
	[-1.09]	[-0.99]	[-1.03]	[-1.02]	[-1.07]
Ret$_{-1w}$	-0.066***	-0.078***	-0.072***	-0.059***	-0.060***
	[-4.81]	[-5.81]	[-5.41]	[-4.50]	[-4.56]
Ret$_{-2w}$	-0.037**	-0.036**	-0.038**	-0.039**	-0.036**
	[-2.54]	[-2.49]	[-2.51]	[-2.54]	[-2.37]
Ret$_{-3w}$	-0.012	-0.010	-0.011	-0.012	-0.012
	[-1.01]	[-0.89]	[-0.96]	[-1.09]	[-1.05]
Ret$_{-4w}$	-0.019*	-0.018*	-0.019*	-0.020**	-0.019**
	[-1.99]	[-1.89]	[-1.93]	[-2.05]	[-2.01]
Ret$_{-2m, -6m}$	-0.009***	-0.009***	-0.009***	-0.010***	-0.009***
	[-3.59]	[-3.42]	[-3.53]	[-3.63]	[-3.53]
Ret$_{-7m, -12m}$	-0.001	-0.001	-0.001	-0.001	-0.001
	[-0.65]	[-0.56]	[-0.64]	[-0.62]	[-0.63]
Constant	0.988	0.993	0.998	0.995	1.006
	[1.16]	[1.16]	[1.17]	[1.17]	[1.18]
No. Obs.	63,475	63,475	63,475	63,475	63,475
Adj-R^2	0.126	0.128	0.126	0.125	0.125
No. Weeks	78	78	78	78	78

Panel D. Future 4-week return					
	(1)	(2)	(3)	(4)	(5)
	$Ret_{1w,\ 4w}$				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.595***	-0.936***	-0.821***	-0.348*	0.460***
	[-4.68]	[-4.72]	[-3.55]	[-1.86]	[4.78]
Beta	-0.047	-0.076	-0.061	-0.042	-0.038
	[-0.12]	[-0.19]	[-0.16]	[-0.10]	[-0.09]
Size	-0.002	-0.001	-0.001	-0.001	-0.002
	[-0.83]	[-0.63]	[-0.61]	[-0.54]	[-0.74]
BM	1.258	1.296	1.332	1.329	1.317
	[0.74]	[0.75]	[0.77]	[0.77]	[0.76]
Margin	-0.898	-0.870	-0.870	-0.853	-0.904
	[-1.25]	[-1.22]	[-1.21]	[-1.18]	[-1.24]
Ret_{-1w}	-0.144***	-0.172***	-0.161***	-0.135***	-0.133***
	[-4.72]	[-6.71]	[-6.13]	[-4.78]	[-4.57]
Ret_{-2w}	-0.074**	-0.072**	-0.074**	-0.076**	-0.070**
	[-2.48]	[-2.37]	[-2.41]	[-2.48]	[-2.24]
Ret_{-3w}	-0.055*	-0.051*	-0.053*	-0.057*	-0.055*
	[-1.89]	[-1.73]	[-1.83]	[-1.98]	[-1.87]
Ret_{-4w}	-0.047**	-0.044*	-0.046*	-0.048**	-0.047**
	[-2.00]	[-1.88]	[-1.94]	[-2.03]	[-2.00]
$Ret_{-2m,\ -6m}$	-0.025***	-0.024***	-0.025***	-0.025***	-0.025***
	[-3.52]	[-3.35]	[-3.40]	[-3.51]	[-3.42]
$Ret_{-7m,\ -12m}$	-0.001	-0.001	-0.001	-0.001	-0.001
	[-0.12]	[-0.10]	[-0.13]	[-0.13]	[-0.13]
Constant	3.008	3.047	3.079	3.081	3.029
	[1.00]	[1.02]	[1.03]	[1.03]	[1.01]
No. Obs.	63,475	63,475	63,475	63,475	63,475
Adj-R^2	0.155	0.157	0.156	0.153	0.153
No. Weeks	78	78	78	78	78

Table 6. Return Predictability of Flows in the Relatively Calm Vs. Volatile Periods

This table shows Fama-MacBeth estimations by regressing future one-week return on weekly stock-level capital flows of different investor groups. We conduct sepatate regressions in the relatively calm period (20140701-20141024), as shown in Panels A and C, and in the more volatile period (20141027-20151231), as shown in Panels B and D. Panels A and B show the univariate results, and Panels C and D additionally control for a battery of stock characteristics, including beta, firm size (size), book-to-market ratio (bm), a dummy variable indicating whether a stock is marginable (margin), and past returns at different horizons (over the past one, two, three, four weeks, as well as 2-to-6 months and 7-to-12 months). Flow for one investor group is calculated as the capital flow at stock level in a given week, scaled by the average total asset holdings of that investor group at the beginning and at the end of the week. For ease of comparison across time periods, we normalize flow by its standard deviation for each investor group in each period. Flow variables are in the unit of basis point (×10000), and the return variables are in the unit of percentage point (×100). WG1 to WG5 indicates investor groups classified by their account values, in the brackets of $<$100K, 100-500K, 500K-3M, 3M-10M, and $>$10M, respectively. All regessions are run at stock-week level, and t-statisitcs, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags.

Panel A. The relatively calm period (2014 Jul-Oct)

	(1)	(2)	(3)	(4)	(5)
	Ret$_{1w}$				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.160**	-0.261***	-0.203***	-0.176***	0.217***
	[-2.63]	[-5.35]	[-5.64]	[-5.14]	[5.39]
Constant	1.699***	1.725***	1.731***	1.733***	1.682***
	[3.94]	[4.06]	[4.07]	[4.07]	[3.92]
No. Obs.	14,190	14,190	14,190	14,190	14,190
Adj-R^2	0.003	0.006	0.005	0.004	0.004
No. Weeks	16	16	16	16	16

Panel B. The volatile period (2014 Oct-2015 Dec)

	(1)	(2)	(3)	(4)	(5)
	Ret$_{1w}$				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.405***	-0.436***	-0.308***	0.001	0.511***
	[-3.22]	[-4.56]	[-3.18]	[0.01]	[5.42]
Constant	1.054	1.112	1.098	1.089	1.061
	[1.05]	[1.12]	[1.10]	[1.09]	[1.07]
No. Obs.	57,481	57,481	57,481	57,481	57,481
Adj-R^2	0.010	0.011	0.012	0.012	0.009
No. Weeks	62	62	62	62	62

Panel C. The relatively calm period (2014 Jul-Oct)					
	(1)	(2)	(3)	(4)	(5)
	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG5
Flow	-0.169***	-0.375***	-0.329***	-0.238***	0.285***
	[-3.45]	[-5.07]	[-4.63]	[-4.93]	[5.87]
Beta	0.327*	0.321*	0.330*	0.334*	0.323*
	[1.90]	[1.97]	[1.97]	[1.97]	[1.92]
Size	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	[-4.16]	[-3.30]	[-3.24]	[-3.40]	[-4.62]
BM	0.432	0.424	0.430	0.437	0.432
	[1.10]	[1.08]	[1.08]	[1.09]	[1.08]
Margin	-0.320	-0.295	-0.278	-0.275	-0.358*
	[-1.70]	[-1.49]	[-1.39]	[-1.42]	[-1.82]
Ret_{-1w}	-0.064**	-0.087***	-0.083***	-0.072***	-0.069***
	[-2.79]	[-3.33]	[-3.38]	[-3.02]	[-3.28]
Ret_{-2w}	-0.032	-0.032	-0.031	-0.032	-0.027
	[-1.43]	[-1.38]	[-1.36]	[-1.38]	[-1.23]
Ret_{-3w}	-0.007	-0.005	-0.005	-0.007	-0.006
	[-0.81]	[-0.55]	[-0.49]	[-0.69]	[-0.64]
Ret_{-4w}	-0.005	-0.004	-0.005	-0.006	-0.005
	[-0.29]	[-0.21]	[-0.28]	[-0.30]	[-0.25]
$Ret_{-2m,\,-6m}$	-0.007*	-0.007	-0.007*	-0.008*	-0.007*
	[-1.87]	[-1.68]	[-1.82]	[-1.93]	[-1.79]
$Ret_{-7m,\,-12m}$	-0.005	-0.005	-0.005	-0.005	-0.005
	[-1.29]	[-1.18]	[-1.22]	[-1.24]	[-1.30]
Constant	1.306**	1.317**	1.312**	1.313**	1.309**
	[2.32]	[2.26]	[2.29]	[2.30]	[2.29]
No. Obs.	13,585	13,585	13,585	13,585	13,585
Adj-R^2	0.072	0.077	0.075	0.074	0.074
No. Weeks	16	16	16	16	16

Panel D. The volatile period (2014 Oct-2015 Dec)					
	(1)	(2)	(3)	(4)	(5)
			Ret_{1w}		
	WG1	WG2	WG3	WG4	WG5
Flow	-0.527***	-0.563***	-0.345***	-0.026	0.426***
	[-7.15]	[-6.53]	[-3.93]	[-0.25]	[4.95]
Beta	-0.225	-0.236	-0.232	-0.223	-0.223
	[-1.07]	[-1.13]	[-1.09]	[-1.06]	[-1.06]
Size	-0.000	-0.000	-0.000	0.000	-0.000
	[-0.42]	[-0.17]	[-0.08]	[0.07]	[-0.08]
BM	0.246	0.274	0.287	0.286	0.284
	[0.38]	[0.41]	[0.44]	[0.44]	[0.44]
Margin	-0.211	-0.193	-0.205	-0.202	-0.201
	[-0.80]	[-0.72]	[-0.78]	[-0.77]	[-0.75]
Ret_{-1w}	-0.067***	-0.076***	-0.069***	-0.056***	-0.058***
	[-4.07]	[-4.84]	[-4.42]	[-3.61]	[-3.64]
Ret_{-2w}	-0.038**	-0.037**	-0.040**	-0.041**	-0.038**
	[-2.20]	[-2.16]	[-2.20]	[-2.23]	[-2.11]
Ret_{-3w}	-0.013	-0.012	-0.013	-0.014	-0.014
	[-0.89]	[-0.81]	[-0.89]	[-0.98]	[-0.96]
Ret_{-4w}	-0.022**	-0.021*	-0.022*	-0.023**	-0.023**
	[-2.05]	[-1.97]	[-1.98]	[-2.11]	[-2.08]
$Ret_{-2m, -6m}$	-0.010***	-0.010***	-0.010***	-0.010***	-0.010***
	[-3.16]	[-3.05]	[-3.12]	[-3.19]	[-3.13]
$Ret_{-7m, -12m}$	-0.000	-0.000	-0.000	-0.000	-0.000
	[-0.14]	[-0.08]	[-0.17]	[-0.14]	[-0.13]
Constant	0.906	0.910	0.917	0.913	0.928
	[0.85]	[0.85]	[0.86]	[0.86]	[0.88]
No. Obs.	49,890	49,890	49,890	49,890	49,890
Adj-R^2	0.140	0.141	0.140	0.138	0.138
No. Weeks	62	62	62	62	62