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Wealth redistribution in bubbles and crashes[☆]

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ABSTRACT

What are the social-economic consequences of financial market bubbles and crashes? Using novel comprehensive administrative data from China, we document a substantial increase in inequality of wealth held in equity by Chinese households in the 2014–15 bubble-crash episode: the largest 0.5% households in the equity market gain, while the bottom 85% lose, 250B RMB through *active trading* in this period, or 30% of either group's initial equity wealth. In comparison, the return differential between the top and bottom household groups in 2012–14, a period of a relatively calm market, is on the order of 1 to 3%. We examine several possible explanations for these findings and discuss their broader implications.

1. Introduction

Global financial markets have witnessed numerous episodes of bubbles and crashes in recent decades.[1] The Chinese stock market, for example, soared nearly 300% in 2006-07 before collapsing 70% the following year; the Indian stock market

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[1] Online Appendix Table A1 summarizes a partial list of boom-bust episodes in the world's largest emerging economies in the past 15 years. Note that we use the term "bubbles and crashes" agnostically to refer to episodes of extreme price movements and trading volume; that is, we do not take a stand on whether asset prices in these episodes can be justified by changes in rational expectations of future cash flows and/or changes in discount rates.

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experienced a similarly spectacular ride between 2005 and 2009. Such repeated emergence of extreme price movements, accompanied by elevated trading volume, has long intrigued economists. Prior research has focused primarily on the formation of bubbles and possible triggers of crashes. Relatively little is known about the social economic impact of financial market bubbles and crashes.[2] A natural question arises: although bubble-crash episodes are often short-lived and fully reversed, do they have long-lasting impact on our society?

We tackle this question by taking the perspectives of ordinary people—e.g., households, pensioners, savers—and examine a novel aspect of the social impact of financial markets: the wealth redistribution role of bubbles and crashes.[3] This is a meaningful empirical exercise for three reasons. First, relative to calm periods, it is less clear, ex-ante, who wins and who loses in bubbles and crashes. On the one hand, it seems natural that wealthier people—who are usually more financially sophisticated and less capital constrained—should outperform the less wealthy in these tumultuous times. On the other hand, wealthier investors tend to accumulate risky securities in market booms (e.g., Hoopes et al., 2017), so may suffer disproportionate losses in crashes.[4]

Second, bubble-crash episodes are almost always accompanied by abnormally high trading volume and return volatilities; in the bubble-crash episode that we analyze, for example, households churn their positions once every three weeks (or nearly 18 times a year). This extraordinary level of turnover, together with the abnormally high market and firm-specific volatilities, can give rise to wealth redistribution at an enormous scale.

The third and perhaps most important reason is that while bubble-crash episodes occur infrequently in developed countries, they are much more common in developing economies.[5] This is all the more worrying given the recent finding (e.g., Malmendier and Nagel, 2011) that salient, early-year experiences affect individuals' economic decisions decades later. Since the majority of the population in developing countries are first-time investors in financial markets, these repeated occurrences of extreme price movements, albeit short-lived, can have long-lasting impact on the behavior and welfare of the hundreds of millions of households in these countries.[6]

Two recent empirical studies (Bach et al., 2020; Fagereng et al., 2020), using annual administrative data of household holdings from Northern European countries, have shown that the rich indeed get richer through financial investments. However, the low-frequency nature of the data makes them less-suited to study wealth redistribution in bubbles and crashes. For one thing, bubbles can emerge and turn into crashes quickly. Second, as emphasized already, bubbles and crashes are accompanied by elevated levels of trading activity. As a result, observing household holdings with annual snapshots yields at best an incomplete (if not misleading) picture of the impact on wealth redistribution.

We contribute to the discussion of the wealth redistribution role of bubbles and crashes by exploiting *daily* administrative data from the Shanghai Stock Exchange (SSE) that cover the *entire* investor population of roughly 40 M accounts. Despite being the world's fourth largest stock market (behind the NYSE, Nasdaq and Tokyo Stock Exchange), the SSE—like other emerging financial markets—is dominated by retail investors; during our sample period, nearly 90% of the trading volume is contributed by retail accounts. Compared to data used in prior studies, our administrative data offer two important advantages. First, our data contain individual accounts' holdings and trading records 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. The granularity and completeness of our data enable us to track the exact amount of capital flows across different investor groups in this market in each day, as well as the resulting gains and losses.

Our main sample covers an extraordinary 18-month 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 5166.35 on June 12th 2015 (including a mild increase from July to October 2014 and a rapid rally from October 2014 to June 2015), before crashing 40% by the end of December 2015. For comparison, we repeat all our analyses using the two-and-half years prior to June 2014, during which the market is relatively calm (as shown in Appendix Fig. A1). Together, our four-year sample with granular observations allows us to carefully analyze the impact of financial investment on wealth redistribution during bubble-crash episodes, and to contrast that with similar impact in calm periods.

[2] A popular view in prior literature is that financial markets are a side show that has a negligible impact on the real economy (e.g., Morck et al., 1990; Blanchard et al., 1993).

[3] Just like prior studies on the wealth effect of financial investment (e.g., Bach et al., 2020; Fagereng et al., 2020), our aim here is to quantify the gains and losses to different investor groups. Put differently, we do not intend to provide an explanation for the price movements in these episodes, which we argue is orthogonal to our calculation of wealth redistribution. Consequently, and following prior research, we take price movements as given throughout the paper.

[4] For example, Sir Isaac Newton, one of the greatest scientists in human history and a lifelong investor, took an aggressive bet near the peak of the South Sea Bubble and lost his lifetime savings of £20,000 in the crash (worth over £3M today). Irving Fisher, one of the greatest American economists, lost everything in the Crash of 1929 after infamously predicting a few days beforehand that stock prices had "reached what looks like a permanently high plateau."

[5] The surge in trading volume (on retail platforms such as the Robinhood app) and market volatilities in the US stock market during the Covid-19 pandemic suggests that our results are also relevant for developed markets. See, for example, https://www.wsj.com/articles/from-1720-to-tesla-fomo-never-sleeps-11594994422.

[6] See Badarinza et al. (2016) and Badarinza et al. (2019) for a literature review of household finance in emerging economies.

For ease of presentation and following the definition used by the China Securities Regulatory Commission, we categorize all household accounts into four groups based on their initial account value with cutoffs at RMB 500 K, 3 M, and 10 M.[7] For the boom-bust period, the bottom group includes 85%, and the top group 0.5%, of all household accounts in our sample and are the focus of this paper. Despite the orders-of-magnitude difference in the number of accounts, the top and bottom groups have similar initial aggregate wealth in the stock market.

We find strong evidence that large investors gain while small investors lose in our bubble-crash episode. Specifically, the bottom 85% households lose 250B RMB due to active trading (i.e., relative to a buy-and-hold strategy) from July 2014 to December 2015, while the top 0.5% gain 254B RMB in this 18-month period. Around 100B of this wealth redistribution can be attributed to gains and losses from trading at the market level (i.e., assume that all investors trade the market portfolio, thus ignoring any heterogeneity in portfolio composition). The remaining 150B RMB of the redistribution is the result of heterogeneous portfolio choice. To put these figures in perspective, the aggregate holding value of the bottom household group is 880B RMB at the end of June 2014, so the cumulative loss in this 18-month period amounts to 28% of their initial wealth in equities. Meanwhile, the aggregate holding value of the wealthiest household group is 808B RMB at the beginning of the sample, so a gain of 31%.

Another way to think about our result is to look at the changes in wealth shares of the various household groups. For example, the top 0.5% of households account for 26% of the household sector equity wealth at the beginning of our sample, which rises to 32% by the end of our sample, or a 6% increase in an 18-month period. On the other end, the bottom 85% account for 29% of the household sector equity wealth at the beginning of our sample and only 22% by the end of the sample. Similar to the exercise in Campbell et al. (2019), we decompose the increase in wealth concentration by the top 0.5% into three parts: returns to initial holdings, cumulative inflows/outflows, and trading-generated gains/losses. The first component contributes little to the increase in wealth concentration by the ultrawealthy as household sectors have similar initial holdings. The second component accounts for 2% of the increase: the ultrawealthy are net buyers of stocks in the bubble-crash episode. The last component (which is our focus in the paper) accounts for the remaining 4%.

In sharp contrast, equity wealth redistribution in calm market conditions is an order of magnitude smaller than that in the bubble-crash episode. For example, for any 18-month subperiod in the two-and-half years prior to June 2014, the ultrawealthy (those in the top 0.5% of the equity wealth distribution) enjoy a gain of up to 8–21B RMB under different benchmarks. These figures translate to percentage gains of 1–3% of the initial equity wealth held by the top household wealth group (compared to 30% in the bubble-crash period). We observe losses of similar magnitudes by the bottom household group in this two-and-half-year period.

In the remainder of the paper and the Online Appendix, we consider a number of possible explanations for our finding that wealth redistribution is amplified in bubble-crash episodes. One natural explanation is that investors with different levels of financial wealth have different rebalancing needs, which are magnified in volatile periods. Indeed, a simple portfolio-choice model that allows for heterogeneous degrees of exposure to the stock market through non-stock investment (e.g., human capital, ownership in private firms) can generate part of the trading pattern documented in the paper. However, such rebalancing-motivated trades—and more generally, any feedback trading strategy that is linear in realized market returns—can only account for a negligible fraction of the observed wealth redistribution among household groups (see Section 2 of the Online Appendix).

We instead argue that our documented pattern of wealth redistribution is partly due to heterogeneity in households' investment skills and/or capital constraints, which are amplified in bubble/crash episodes. Through a simple return attribution exercise, we show that nearly half of the 100B RMB redistribution from small to large investors at the market level is due to differences in their market timing ability, and the other half to the wealthy's larger average exposure to the stock market over the entire sample period.

In the cross-section of stocks, we find that trading by the bottom 85% households significantly and negatively forecasts future stock returns, while that by the top 0.5% positively predicts stock returns. For example, in a simple Fama-MacBeth regression, a one-standard-deviation increase in weekly flows into a stock by the top household wealth group predicts a 0.44% (t-statistic = 6.20) higher return in the following week, and that by the bottom household group predicts a lower return of −0.48% (t-statistic = −4.80). The difference of 0.93% (t-statistic = 7.94) in weekly returns is both economically large and statistically significant.

More importantly, the difference in return predictability—per one-standard-deviation change in flows—between large and small investors in the bubble-crash period is more than four times larger than that in the calm period. Specifically, in the same Fama-MacBeth regression for the period January 2012 to June 2014, the corresponding point estimates are 0.08% for the top household group and −0.12% for the bottom household group, with a difference of 0.19%. In other words, the impact of heterogeneity in investment skills on household wealth concentration is greatly amplified when market volatilities and trading volume are high.

[7] The total account value includes equity holdings in both the Shanghai and Shenzhen Stock Exchanges as well as cash in the account. For our main sample, between July 2014 and December 2015, this wealth classification is done at the end of June 2014. For the sample of January 2012 to June 2014, the classification is done at the end of December 2011.

2. Related literature

Our paper contributes to the debate on the real effect of financial markets. A popular view in prior literature is that financial markets are a side show that has negligible impact on the real economy. Morck et al. (1990) and Blanchard et al. (1993) argue that fluctuations in stock valuation do not affect real investment. This view seems naturally applicable to bubble-crash episodes. Take the Internet bubble for example, by the end of 2000, the Nasdaq index fell virtually to its pre-bubble level; 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., Pástor and Veronesi, 2009). Our paper contributes to this literature by examining a novel aspect of the social-economic consequences of financial market bubbles and crashes—how these periods of extreme return volatilities and trading volume affect the distribution of financial wealth, which can have long-lasting impact on many facets of the society.

Our paper also sheds light on investor portfolio choice during bubbles and crashes.[8] 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. 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 2008 global financial crisis. While our results on investor trading behavior confirm these prior findings, our focus is squarely on the wealth redistribution between the poor and wealthy using our comprehensive daily holdings and transaction data.[9] Note that although we focus on one specific instance of bubble-crash episodes (like most prior empirical studies in this literature), the richness of our data allows us to a) compare the gains and losses across investor groups, b) examine the mechanisms that drive wealth redistribution, and c) most importantly, uncover a novel amplification of skill heterogeneity and wealth redistribution during extreme market conditions, which can have broader implications for other time periods and financial markets.

Our paper is also related to the recent empirical literature on return differentials between the poor and wealthy (especially the ultra-wealthy) in financial markets. Bach et al. (2020) and Fagereng et al. (2020), using annual administrative data of household portfolios in Northern European countries, find that the wealthiest 1% of the population earn an annual investment return that is more than 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 in each year over a long period of time, with the assumption that investors trade once a year on December 31st. Campbell et al. (2019), exploiting monthly household stock market investment data from India, also show that the rich get richer (and the poor become poorer) due to differences in portfolio diversification.[10] Our study complements this literature by examining the degree to which investment returns drive financial wealth inequality in bubble-crash episodes.

Our results also contribute to the debate on stock market participation. One of the most robust findings across developed and developing nations is that although the stock market offers a high average return and has a low correlation with the rest of a typical household portfolio, many households have been reluctant to invest in the stock market (e.g., Haliassos and Bertaut, 1995; Barberis and Thaler, 2003). Consequently, policymakers in many countries, especially those in developing nations, have been pushing for greater stock market participation (or more inclusive financial markets). Our results call for a re-evaluation, or at least rethinking, of such policies. On the one hand, passive investment in the stock market is potentially beneficial to anyone—even those with low financial literacy, as it allows investors to earn the equity risk premium. On the other hand, households in developing markets tend to be active investors, like the 40 M household accounts in the Chinese market; consequently, greater market participation, if not managed properly, can be detrimental to individual welfare.

Finally, our study contributes to the recent discussion of rising wealth inequality. Atkinson et al. (2011), Alvaredo et al. (2013, 2018), Piketty (2014, 2015), and Piketty et al. (2019) provide compelling evidence of a worldwide surge in wealth concentration in the last fifty years.[11] The rise in wealth inequality can be in part due to an increase in income disparity, but it may also be driven by bequests and by heterogeneous returns from financial investments. To the extent that stock wealth and total wealth are positively correlated, our results provide further evidence for this capital-investment channel. The ultra-wealthy, those in the top 0.5% of the wealth distribution in the stock market, likely have better access to both information and capital than the rest of the market; consequently, they enjoy a disproportionate share of the total return on capital. The main takeaway of our paper is that this effect is greatly amplified in financial bubbles and crashes (when market volatilities and trading volume peak), leading to an even higher degree of wealth concentration.

[8] More generally, our results are related to the vast literature on investors' trading behavior and common mistakes in their trading decisions in financial markets (e.g., Odean 1999; Calvet et al., 2007, 2009a, 2009b; Chen et al., 2019; Cai, He, Jiang, and Xiong, 2020; Li et al., 2021).

[9] That prior researchers are only able to observe a non-representative subset of the investor universe (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.

[10] Relatedly, Barber et al. (2009) show that retail investors in aggregate lose to institutions in the setting of the Taiwan Stock Market. Sakong (2019) provides evidence that relative to wealthy household, poor households "buy high and sell low" in the housing market, which contributes to increasing wealth inequality in the US.

[11] Both the popular press and academic research have linked this widening wealth inequality to adverse social outcomes, including social unrest, political populism, regional crimes, and mental health issues (e.g., Pickett and Wilkinson, 2019).

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 has much in common with other developing markets. 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 (which we confirm in our data). Given the striking similarities between the Chinese stock market and other developing markets (in terms of retail ownership, trading activities, regulatory environments, etc.), we believe that our results have broader implications for emerging economies. As such, our exercise provides a useful first step to understanding the heterogeneity in household experience during these tumultuous periods.

3.1. Data sources and summary statistics

We obtain daily administrative data from the Shanghai Stock Exchange, which cover the entire investor population of around 40 M accounts. More specifically, our account-level data are compiled by the China Securities Depository and Clearing Corporation (CSDCC) 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 important advantages. First, our data contain individual accounts' holdings and trading records, at the firm level, at a daily frequency.[12] Second, the holdings of all investors in our sample sum up to exactly each firm's total tradable shares; the buy transactions and sell transactions in our sample also sum up to the daily trading volume in the Exchange.

For ease of computation and presentation, we aggregate the 40 M accounts in our sample into various investor groups. At the broadest level, we classify all accounts into three categories: those owned by households, institutions, and corporations. (Account type and ownership information is directly observable in our administrative data.) The last category includes both cross holdings by other firms and ownership by government-sponsored entities. Household accounts are further stratified into four groups based on account value (defined as the sum of equity holdings in both Shanghai and Shenzhen stock exchanges and cash in the account) with the following cutoffs: below 500 k RMB (WG1), 500 k to 3 million RMB (WG2), 3 million to 10 million RMB (WG3), and above 10 million RMB (WG4).[13]

For household accounts that exist before July 2014, the classification is done on June 30th, 2014, based on the maximum portfolio value in the year prior to the beginning of our sample (so from July 2013 to June 2014), which is then 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 are opened after July 2014, we classify these new entrants into the same four wealth groups every six months. For example, for accounts opened between July and December 2014, we sort them into four groups based on maximum account value between July and December of 2014.

Panel A of Table 1 reports the summary statistics of the account value, capital weights, and trading volume of all investor groups. Investors in the SSE collectively hold a market value of 13T RMB on July 1st, 2014, which then 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 11%, and households the remaining 25%. Although owning most of the market, corporations rarely trade and account for only 2% of trading volume; retail investors, in contrast, contribute 87% of daily volume. Institutions account for the remaining 11%. Within the household sector, the four wealth groups include 85, 12.5, 2, and 0.5% of all households in our sample. At the beginning of our sample (July 2014), the capital shares of the four household groups (in increasing order of equity wealth) are 29%, 29%, 16%, and 26%, respectively; at the end of our sample, the corresponding figures are 22, 29, 17, and 32%. The four household groups account for 21.1, 26.6, 15.9, 23.0% of the trading volume during this period, similar in magnitude to their capital shares. This suggests that households in different equity wealth groups a) have similar propensity to trade, and b) incur similar transaction costs (so differences in transaction costs are unlikely to explain the documented differences in their return).

We also obtain complete administrative records of investor holdings and trading for the period January 2012 to June 2014, during which the Chines stock market is relatively calm. (Online Appendix Fig. A1 plots the Shanghai Composite Index from January 2012 to December 2015.) We classify all households (roughly 40 M accounts) in this calm period into four wealth groups based on individual account value at the end of December 2011 following the same methodology described above. The four wealth groups (from the smallest to largest) account for roughly 75, 20, 4.5 and 0.5% of all households in this sample. In terms of aggregate equity wealth, the four wealth groups hold on average 575B, 770B, 794B, 673B RMB worth of stocks during this period, or 20.3, 27.4, 28.3, and 24% of the entire household sector.

Panel B of Table 1 shows portfolio style tilts of households in different wealth groups, and Panel C reports the pairwise correlations in trading across investor groups (defined as weekly trading in individual stocks divided by the number of shares

[12] Although we do not observe margin borrowing in our administrative data, this does not affect our calculation of RMB gains and losses experienced by different investor groups.

[13] These cutoffs are chosen (and the total holding value across the two exchanges computed) by the China Securities Regulatory Commission to identify large vs. small investment accounts.

Table 1
Summary Statistics
Panels A, B, and C present summary statistics on account value, trading volume, and initial portfolio tilts by different investor groups in the bubble-crash period. The entire investing population is classified into three broad categories: households, institutions, and corporations. Within the household sector, investors are further classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value); WG1 to WG4 include investors whose total account value fall into the brackets of <500K, 500K-3M, 3M-10M, and >10M, respectively. Panel A reports summary statistics on account value and trading volume (in billions of RMB). The initial account value and capital weight are calculated on July 1st, 2014. The average account value and trading volume refer to the time series average in our entire sample period. Panel B shows portfolio style stilts of different household wealth groups at the beginning of our sample. Specifically, we regress stock-level portfolio weights of each household group – adjusted by the portfolio weights of the entire household sector – on beta, firm size (size), and book-to-market ratio (bm). Panel C shows the weekly pairwise correlations in trading, defined as the net trading in individual stocks divided by the number of shares tradable, of each household group as well as that of money managers (mutual funds plus hedge funds), averaged across our sample period.
Panel D provides an approximate mapping between equity wealth and total wealth using data from the 2014 survey of the China Family Panel Studies (CFPS), as well as Piketty, Yang, and Zucman's (PYZ, 2018) estimates of the total wealth distribution in China. The first three columns present the stock market participation rates for various brackets of household wealth. Column (1) shows the participation rate estimated using the CFPS data, and Columns (2) and (3) report the fraction of equity investors in China that are from each wealth bracket, calculated using equation (1). The next three columns present an approximate mapping between households' total wealth and their equity wealth. Column (4) shows the thresholds of the wealth distribution, taken from PZY (2018). Column (5) reports the average fraction of total wealth invested in risky financial assets for each wealth bracket using the CFPS data. Column (6) then shows our estimated value of risky financial holdings at each of the wealth threshold, by multiplying Column (4) by Column (5). For households in the top 0.1% and 0.01% of the wealth distribution, given the small number of observations in CFPS, we extrapolate the participation rate and portfolio weight in risky financial assets from the top 1% group.

Panel A. Account value and trading volume

	HHs	Inst	Corps	WG1	WG2	WG3	WG4
initial aggregate holdings (B)	3048	1496	8898	880	869	491	808
initial capital weight	22.7%	11.1%	66.2%	6.5%	6.5%	3.7%	6.0%
average aggregate holdings (B)	5797	2567	14386	1322	1640	1002	1834
average capital weight	25.1%	11.3%	63.6%	5.9%	7.1%	4.3%	7.8%
end-of-period aggregate holdings (B)	6436	3114	15948	1414	1835	1106	2082
end-of-period capital weight	25.2%	12.2%	62.5%	5.5%	7.2%	4.3%	8.2%
capital weight within households							
at the beginning (Jul. 1st, 2014)				28.9%	28.5%	16.1%	26.5%
at the peak (Jun. 12th, 2015)				20.4%	27.8%	17.8%	34.0%
at the end (Dec. 31st, 2015)				22.0%	28.5%	17.2%	32.3%
% of number of accounts				84.9%	12.6%	1.9%	0.5%
average daily volume (B)	376	50	8	91	115	69	100
average volume share	86.6%	11.7%	1.7%	21.1%	26.6%	15.9%	23.0%

Panel B. Initial portfolio style tilts: regressing initial excessive portfolio weights on stock characteristics

	$\omega_0 \times 100$				
	WG1	WG2	WG3	WG4	WG4-WG1
Beta	0.001	0.010***	0.008***	-0.017**	-0.018**
	[0.19]	[3.71]	[2.83]	[-2.28]	[-2.06]
Size	-0.006***	-0.004***	0.002	0.010***	0.016***
	[-3.53]	[-4.03]	[1.60]	[3.49]	[4.80]
BM	0.045***	0.016***	-0.009***	-0.060***	-0.105***
	[10.09]	[5.78]	[-2.86]	[-8.13]	[-12.15]
No. Obs.	947	947	947	947	
R^2	0.098	0.057	0.018	0.071	

Panel C. Pairwise correlations of trading

	WG1	WG2	WG3	WG4	MFs & HFs
WG1	1				
WG2	0.61	1			
WG3	0.24	0.56	1		
WG4	-0.27	-0.26	0.02	1	
MFs & HFs	-0.26	-0.28	-0.26	-0.03	1

Panel D. Stock market participation and equity wealth across wealth groups

	Stock Market Participation			Investment in Risky Financial Assets		
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth Percentile	Participation Rate	% Stock Investors	Cumulative % Stock Inv	Wealth Threshold	Avg. wght in Risky Fin Assets	(4) × (5)
p0-p50	1.4%	16.2%	16.2%	0	23.7%	0
p50-p60	2.6%	6.2%	22.4%	84,932	16.9%	14,371
p60-p70	3.6%	8.6%	30.9%	115,449	5.5%	6,401
p70-p80	7.1%	16.7%	47.6%	158,650	6.9%	10,892
p80-p90	8.0%	18.9%	66.5%	236,027	8.8%	20,878
p90-p100	14.3%	33.6%	100%	420,197	9.4%	39,454
top 5%	14.8%	17.4%		1,102,608	8.3%	91,564
top 1%	15.2%	3.6%		2,979,431	10.2%	302,435
top 0.1%	15.2%	0.4%		7,988,140	10.2%	810,857
top 0.01%	15.2%	0%		67,744,170	10.2%	6,876,546

tradable, of each household group as well as that of professional money managers, averaged across our sample period). We discuss these summary statistics in greater details in Section 1.1 of the Online Appendix.

3.2. Data limitations

Our data also have several limitations. First, we do not observe households' wealth allocations in other markets, such as real estate and bank savings products. Although direct equity holdings are only one component of total household wealth, it is likely that total wealth and equity wealth are positively correlated. Data from the 2014 survey of the China Family Panel Studies (CFPS), conducted by the Institute of Social Science Survey at Peking University, confirm a correlation between total wealth and equity wealth of 0.46 and an elasticity of total wealth to equity account value of 0.15 among market participants in the Chinese economy.[14]

We also provide an approximate mapping between the distribution of equity wealth held by Chinese households and that of their total net wealth, using data from the 2014 CFPS and estimates of the wealth distribution in China by Piketty et al. (2019) (as shown in Table 1 Panel D and described in Section 1.2 of the Online Appendix). Two facts are worth pointing out here. First, stock market participants are drawn from the whole distribution of household wealth. For example, nearly half of stock investors are from the bottom 80% of the wealth distribution. Second, given the positive correlation between equity wealth and total net worth, the 0.5% threshold in the equity wealth distribution (the focus of this paper) corresponds roughly to the 0.1-0.01% cutoff in the total wealth distribution.

Second, and relatedly, we do not observe households' holdings of equity mutual funds. This is not a major concern for our purpose because during our sample period mutual funds hold 3% of the equity market and account for less than 3% of the trading volume (in comparison, retail investors contribute nearly 90% of the trading volume). Third, we do not have information on margin borrowing by individual accounts. This, however, does not impact our calculation of gains and losses in RMB terms experienced by different investor groups. Finally, we do not observe holdings and transactions in stock index futures. However, the futures market is dominated by a small number of large institutions so has little impact on the majority of Chinese household investors.

4. Wealth redistribution in a bubble-crash episode

Conceptually, each investor's (or investor group's) end-of-period stock market wealth can be decomposed into four parts: a) initial stock holdings at the beginning of our sample; b) capital flows into and out of the stock market (i.e., through trading) in our sample period; c) initial-holdings-generated gains and losses following a buy-and-hold strategy (which are equal to initial holdings multiplied by subsequent cumulative returns); and d) capital-flow-generated gains and losses (which are the sum of each RMB invested multiplied by its corresponding cumulative return from the day of investment to the end 2015, see Eq. (5)).

It is useful to note that buy-and-hold strategies (corresponding to component c) above) are not a zero-sum game. In the classic CAPM framework, for example, all investors hold the market portfolio and earn the market return, which is on average positive. In other words, component c) can be positive for all investors as the market value grows. In our data, household groups hold similar stock portfolios at the beginning of July 2014, so there is little variation in their initial-holdings-generated gains and losses (which are largely determined by the market return in our sample period). In contrast, active trading (corresponding to component d) above) is a zero-sum game – if someone is buying, someone else is selling. In other words, flow-generated gains sum up to exactly zero if the flows (or trading) sum up to zero. (In practice, investor trading does not always sum up to zero because of share issuance and conversions of non-tradable to tradable shares.)

Consequently, we focus on gains and losses resulting from households' trading activity (component d) in the above decomposition) throughout this paper, and interpret them through the lens of wealth redistribution. More specifically, we employ two benchmarks to evaluate households' trading activity and the ensuing gains and losses. The first benchmark is a buy-and-hold investor with the same initial holdings as the household group in question. The second benchmark assumes that household groups' trading is proportional to their initial capital weights.

4.1. Capital flows by different investor groups

We start by comparing each investor group to a buy-and-hold investor with the same initial holdings in the stock market; that is, we focus on the trading activity of each investor group. Trading in (or capital flow to) each stock s by investor group g on day t is calculated as the value of the stock holding at the end of day t minus that at the end of day t-1 multiplied by

[14] We follow Campbell, Ramadorai, and Ranish (CRR, 2019) to estimate the correlation and elasticity of total wealth to equity account value; CRR (2019) report a correlation of 0.3 and an elasticity of 0.15 among Indian stock holding households in 2012. The CFPS survey in China does not collect information on the value of equity holdings; instead, it asks for the value of all financial products (including stocks, mutual funds, bonds, other derivatives, etc.); stocks holdings are by far the most common form of household financial investment reported in the survey, and for more than half of the survey respondents the only form of financial investment.

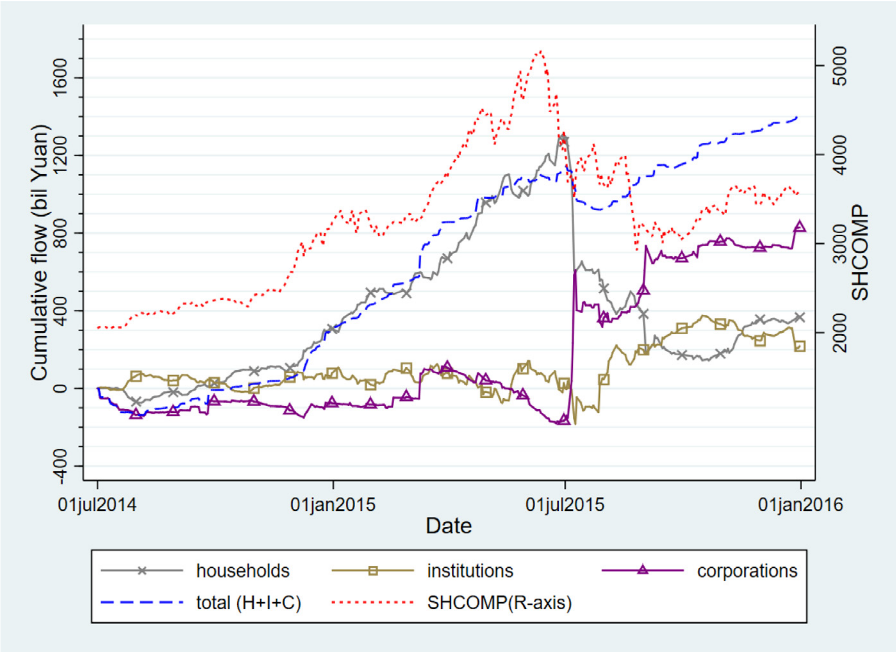

Fig. 1. Anatomy of Flows: Cumulative Flows by Investor Sectors. This figure shows cumulative capital flows to the stock market by different investor sectors—households, institutions, and corporations—as well as the sum of their flows (which is equal to the total increase of tradable shares in the market) from July 2014 to December 2015. Capital flows are in billions of RMB, and are plotted against the left y-axis. The Shanghai Composite Index is plotted against the right y-axis.

the stock return on t:[15]

$$flow_{g,s,t} = \left(shares\ held_{g,s,t} \times price_{s,t} - shares\ held_{g,s,t-1} \times price_{s,t-1} \times ret_{s,t}\right) \tag{1}$$

Summing across all stocks in the market, we get

$$flow_{g,t} = \sum_{s} flow_{g,s,t} \tag{2}$$

By construction, the total capital flow, summed across all investor sectors, is equal to the aggregate increase of tradable shares in the market less the amount of cash dividends distributed to investors (the latter is roughly 0.6T RMB). During our sample period (July 2014 to December 2015), the total increase of tradable shares in the market amounts to 2T RMB, 1.5T of which is due to the conversion of restricted shares into tradable shares owned by corporations (mostly SOEs), and the remaining 0.5T of which is due to IPOs, SEOs, and the conversion of convertible bonds.

Fig. 1 shows an anatomy of daily cumulative capital flows by investor sectors—households, institutions, and corporations. From July 1st, 2014 to June 12th, 2015, the household sector has a cumulative inflow of 1.1T RMB, while the other two sectors have cumulative inflows of 80B and −130B, respectively. Household inflows keep rising until June 29th, 2015, at a peak of 1.3T RMB. Shortly after that, the household sector starts to sell off their shares to corporations, mainly government-sponsored investment vehicles. These government-related entities are instructed by market 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 12th, corporations have a cumulative inflow of 950B RMB, while the household sector has an outflow of 800B.

We then zoom in on capital flows of the household sector (particularly across different wealth groups within the household sector). The top panel of Fig. 2 shows the daily cumulative flows of the four household groups sorted by account wealth. There is a *positive* monotonic relation between account value and capital flows during the boom period. Households in the top wealth group allocate the most capital to the stock market while those in the bottom group reduce their stock market exposure in the boom period. The other two groups of households are somewhere in between. At the market peak on June 12th, 2015, the four household groups, from the smallest to the largest, have cumulative flows to the stock market of −128B, 280B, 282B, and 709B RMB, respectively. Shortly after the peak, the wealthy quickly exit the market, selling their

[15] We determine investors’ daily trading by the change in holdings between two consecutive days, rather than aggregating exchange-reported buy and sell transactions. This is because changes in holdings include not only transactions in the exchange during trading hours, but also transactions and transfers of ownership taking place after market close and/or off the exchange: for instance, block trades, distributions, rights issues, and new share allocations (from IPOs and SEOs). We adjust the price and number of shares held for shares splits, stock dividends, and other corporate events.

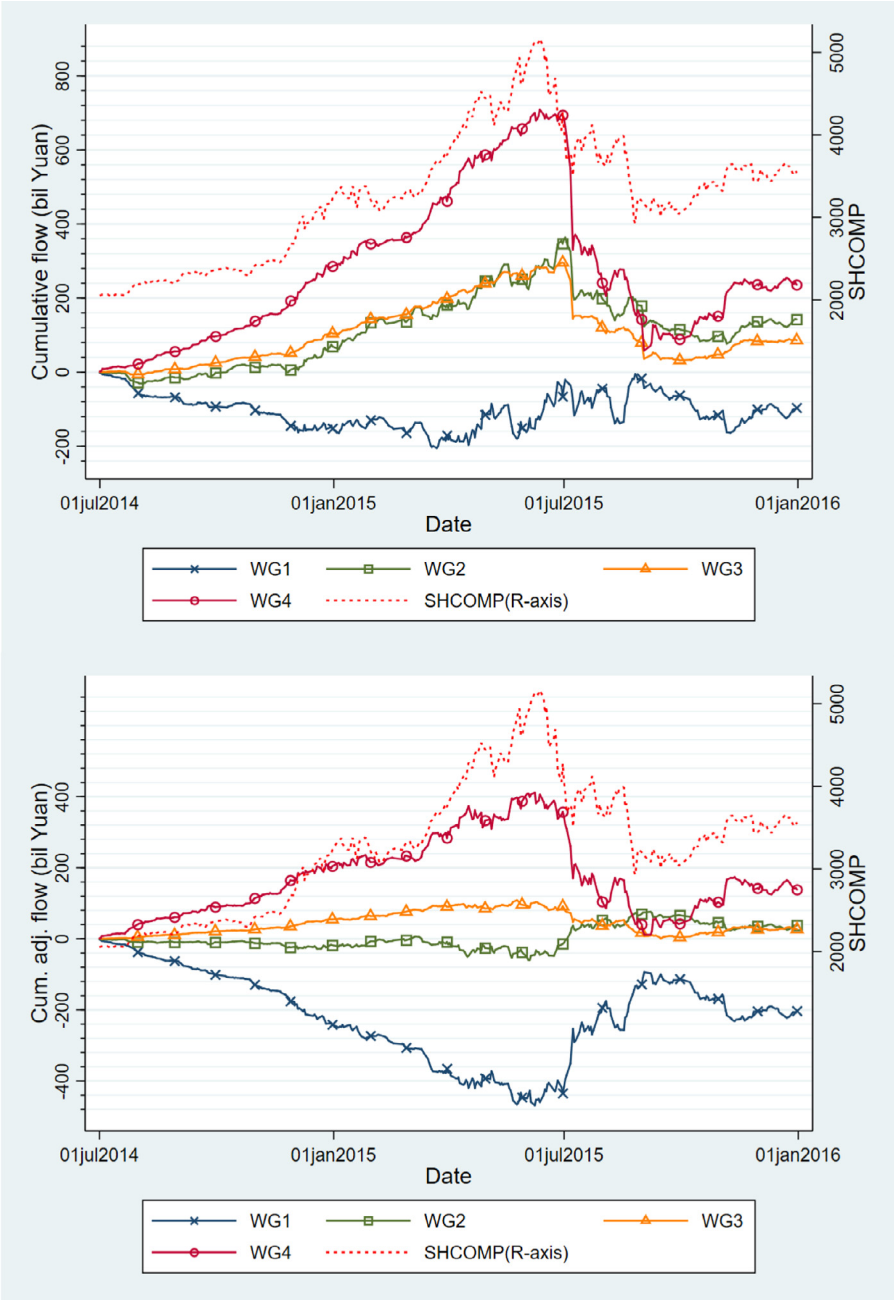

Fig. 2. Cumulative Flows of Households in the Bubble-Crash Period. This figure shows cumulative capital flows by different wealth groups in the household sector. The top figure shows the raw value of flows, and the bottom figure shows adjusted flows. Households are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value), with cutoffs at RMB 500 K, 3 M, and 10 M. WG1 includes investors with account value less than 500 K, and WG4 includes investors with account value greater than 10 M. In the bottom figure, we adjust the raw value of flows of 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 Eqs. (3) and (4)). Capital flows are in billions of RMB, and are plotted against the left y-axis. The Shanghai Composite Index is plotted against the right y-axis.

shares partly to smaller households and partly to corporations. In the bust period of June to December 2015, the four groups have cumulative capital flows of 32B, −137B, −196B, and −473B RMB, respectively.

One potential concern with the way flows are constructed is that the four household groups have different aggregate equity wealth to start with. Even if all households have the same trading propensity, we may mechanically observe different trading activities because of the differences in their initial wealth in the equity market. To address this, we employ a second benchmark, the proportional-trading benchmark, in which we compare the trading activity of each household group with a fraction of the aggregate trading by the household sector where the fraction is proportional to the initial equity-wealth share of the household group in question. For example, the top wealth group accounts for 26.5% of the total equity wealth of the household sector at the beginning of our sample, we then subtract in each day the trading activity of the top wealth group by 26.5% of the aggregate trading of the household sector. We label this difference the *adjusted flow*. The adjusted flow by household group g in stock s is then defined as:

$$adj\_flow_{g,s,t} = flow_{g,s,t} - \omega_g \sum_g flow_{g,s,t}, \tag{3}$$

where w_g is the initial wealth weight in the equity market of household group g, which sums up to one across the four groups. Adjusted flows therefore capture excess relocation into and out of each stock and, by construction, sum up to zero across household groups every day. Summing over all stocks in the market, we have

$$adj\_flow_{g,t} = \sum_s Adj\_flow_{g,s,t}. \tag{4}$$

The bottom panel of Fig. 2 shows the cumulative adjusted flows to the market by different household groups. Again, there is a *positive* monotonic relation between account value and adjusted flows. The wealthiest group 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 (WG4) and second wealthiest (WG3) groups peak on June 8th and May 25th, 2015 at 411B and 108B RMB, respectively, a few weeks before the market peak (June 12th, 2015). On June 12th, the cumulative adjusted flows of the four groups, in increasing order of account wealth, are −460B, −45B, 98B, and 406B, respectively. The wealthier groups then exit the market shortly after the market peak. In a little over two months, from Jun 12th to Aug 26th, the Shanghai Composite Index drops from a peak of 5166 to a trough of 2927. During this period, the adjusted flows of the four groups are 328B, 117B, −79B, −365B, respectively. The market then rebounds to close at 3539 on December 31st, 2015. From the peak to the end of our sample, the four household groups have cumulative adjusted flows of 257B, 83B, −71B, −268B, respectively.

4.2. Flow-Generated gains and losses

After documenting households' flow patterns, we then quantify the resulting gains and losses. We focus on RMB gains and losses—the quantity that ultimately matters to investors—instead of portfolio returns, because the amount of capital invested in the stock market fluctuates dramatically in our sample period. To the extent that the amount of invested capital and subsequent portfolio returns are correlated, the time-series average portfolio return can be a misleading statistic which does not reflect the actual experience of the investor (Dichev, 2007). (That said, we analyze portfolio returns in the next section to better control for common risk exposures.) More specifically, to track wealth redistribution in our sample, we calculate stock-specific flow-generated gains for each household group up to any given day by interacting daily flows (both actual and adjusted) to a stock prior to that day with the subsequent stock return until that day. We then sum this up across all stocks in the household portfolio to derive the total gains and losses for each household group. Our calculation does not depend on any assumption about the holding horizon, and reflects investors' actual RMB gains and losses through trading.[16] More formally, we define cumulative flow-generated gains by group g up to day t as

$$cum\_flow\_gen\_gains_{g,t} = \sum_s \sum_{\tau \le t} flow_{g,s,\tau} \times ret_{s,\tau,t} \tag{5}$$

where $flow_{g,s,\tau}$ is the capital flow of group g to stock s in day τ, and $ret_{s,\tau,t}$ is the cumulative return of stock s between τ and t. Similarly, cumulative adjusted-flow-generated gains are defined as

$$cum\_adj\_flow\_gen\_gains_{g,t} = \sum_s \sum_{\tau \le t} adj\_flow_{g,s,\tau} \times ret_{s,\tau,t}. \tag{6}$$

Fig. 3 presents the cumulative-flow- (the top figure) and cumulative-adjusted-flow- (the bottom figure) generated gains of the four household groups. Based on unadjusted flows in the entire period, the four household groups have cumulative gains of −250B, −42B, 44B, and 254B, respectively. The corresponding figures based on adjusted flows are −252B, −44B, 43B, and 252B, respectively.[17] Relative to the groups' aggregate account value at the beginning of our sample, this wealth redistribution amounts to a 28% loss of the initial account value for the bottom 85% of households, and a net gain of 31% for the top 0.5%.[18]

A natural question to ask is how much of this wealth redistribution is due to capital flows simply going into and coming out of the stock market and how much is due to heterogeneity in portfolio composition. To quantify the impact of market-level flows, we assume that every RMB invested in stocks tracks the market index. Flow-generated gains at the market level

[16] Our method tracks the capital gains and losses when the investor is actually holding the stock—from the time she buys to the time she sells. For instance, consider an investor who buys a stock in day 1 and liquidates her position in day 3. Our *cum_flow_gen_gains* is then equal to the purchase value times the stock return from day 1 to day 3.

[17] As can be seen from the figure, our results are quantitatively similar if we calculate the wealth redistribution using an alternative start date of the sample (e.g., 201408) or an alternative end date (e.g., 201510).

[18] Excluding trading by top executives in publicly traded firms in China from that of the top equity wealth group has virtually no impact on the imputed gains. There is also an insignificant correlation between trading by top executives and that by the top wealth group.

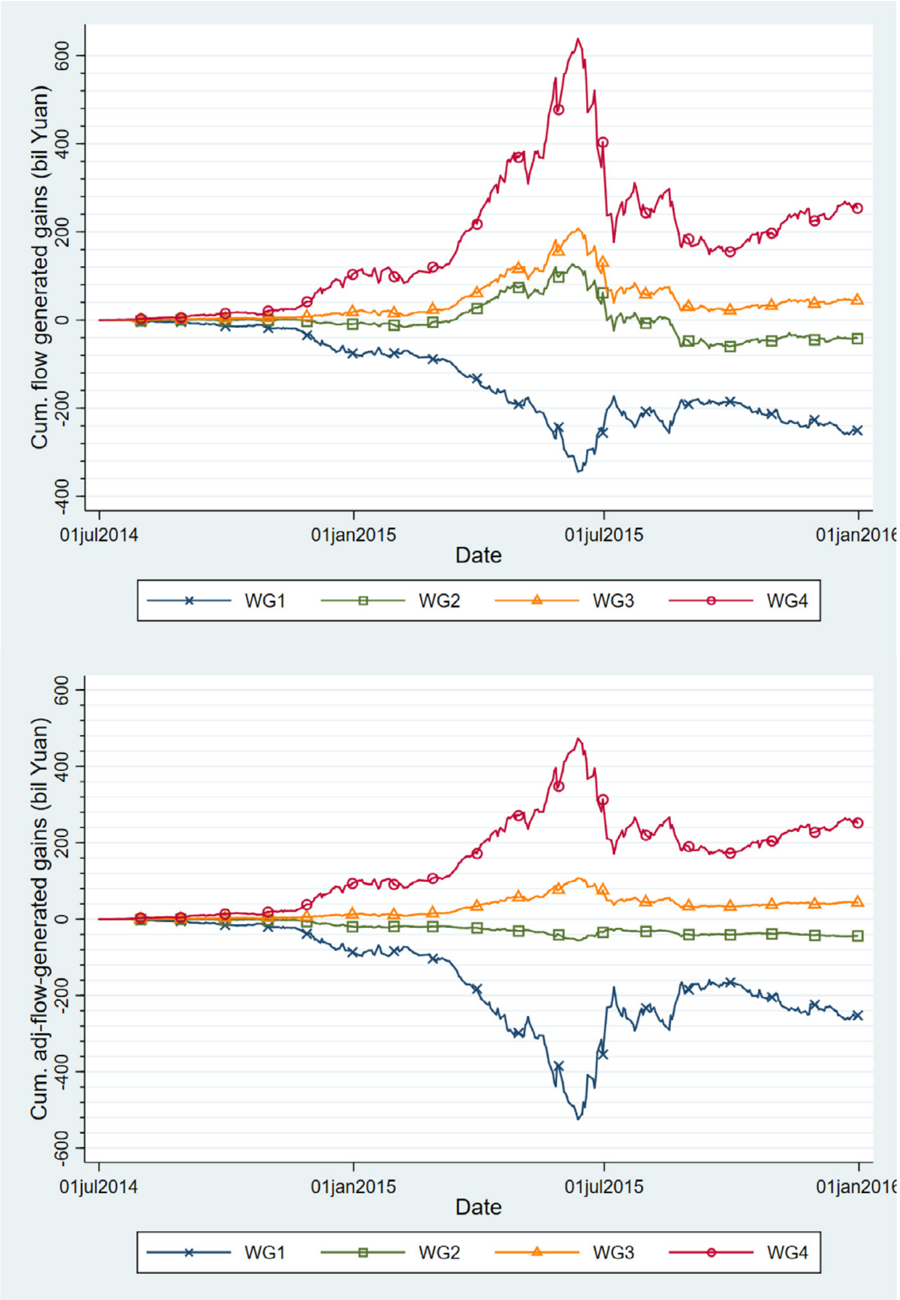

Fig. 3. Flow-Generated Gains of Households in the Bubble-Crash Period. This figure shows cumulative flow-generated gains by different wealth groups in the household sector. The top figure shows flow-generated gains/losses, and the bottom figure shows adjusted-flow generated gains/losses. Households are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value), with cutoffs at RMB 500, 3, and 10 M. WG1 includes investors with account value less than 500 K, and WG4 includes investors with account value greater than 10 M. We calculate the cumulative (adjusted-) flow-generated gains of each household group by multiplying daily flows to a stock with the subsequent stock return (till the day in question), and then summing this up over all days till the day in question and across all stocks in the household portfolio (see Eqs. (5) and (6)). Capital gains are in billions of RMB.

are then calculated as the product of daily flows and subsequent market returns. Specifically, the cumulative flow-generated gain driven by market-level flows up to day t for investor group g is equal to

$$cum\_flow\_gen\_gains^{mkt}_{g,t} = \sum_{\tau \le t} flow_{g,\tau} \times ret^{mkt}_{\tau,t} \quad (7)$$

Table 2
Summary of Capital Flows and Flow-Generated Gains
Panel A of this table reports capital flows (Panel A1) and flow-generated gains (Panel A2) of different household wealth groups in the bubble-crash period. Within the household sector, investors are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value); WG1 to WG4 include investors whose total account value fall into the brackets of <500K, 500K-3M, 3M-10M, and >10M, respectively. For comparison, Panel A3 shows cumulative flow-generated gains of various household wealth groups in the two-and-half years prior to our main sample (201201 to 201406), during which the market is relatively calm.
Panel B reports aggregate capital flows (Panel B1) and flow-generated gains (Panel B2) for the three sectors: households, institutions, and corporations, as well as those of mutual funds and state-owned corporations. Both capital flows and flow-generated gains are in billions of RMB.

	WG1	WG2	WG3	WG4	
Panel A1. Capital flows (Bil. RMB)					
boom period (140701-150612)					
flow into the market	-128	280	282	709	
adjusted flow into the market	-460	-45	98	406	
bust period (150612-151231)					
flow into the market	32	-137	-196	-473	
adjusted flow into the market	257	83	-71	-268	
the entire period (140701-151231)					
flow into the market	-96	142	86	236	
adjusted flow into the market	-203	38	27	138	
Panel A2. Flow-generated gains in the bubble-crash period: 2014 Jul. – 2015 Dec. (Bil. RMB)					
flow-gen gains (total)	-250	-42	44	254	
adj-flow-gen gains (total)	-252	-44	43	252	
flow-gen gains at the market level	-118	-28	16	84	
adj-flow-gen gains at the market level	-104	-15	23	96	
Panel A3. Flow-generated gains in calm market conditions (Bil. RMB)					
2012 Jan. - 2013 Jun.					
flow-gen gains (total)	-35	-16	-8	8	
adj-flow-gen gains (total)	-27	-1	8	21	
2012 Jul. - 2013 Dec.					
flow-gen gains (total)	-12	-17	-13	-1	
adj-flow-gen gains (total)	-6	-5	0	10	
2013 Jan. - 2014 Jun.					
flow-gen gains (total)	-23	-20	-14	1	
adj-flow-gen gains (total)	-14	-4	3	15	
	HHs	Inst.	Corp.		
				MFs	State-Owned Corp.
Panel B1. Capital flows (Bil. RMB)					
boom period (140701-150612)					
flow into the market	1142	78	-126	-116	-36
bust period (150612-151231)					
flow into the market	-775	138	952	-52	873
the entire period (140701-151231)					
flow into the market	368	216	826	-167	836
Panel B2. Flow-generated gains in the bubble-crash period: 2014 Jul. – 2015 Dec. (Bil. RMB)					
flow-gen gains (total)	6.7	252.3	112.9	37.9	75.4
flow-gen gains at the market level	-46.1	65.2	34.8	2.0	25.3

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

$$cum\_adj\_flow\_gen\_gains^{mkt}_{g,t} = \sum_{\tau \le t} adj\_flow_{g,\tau} \times ret^{mkt}_{\tau,t} \tag{8}$$

The top panel of Fig. 4 shows the market-level cumulative flow-generated gains for the four household groups sorted by account value: during this one-and-half-year period, the four household groups accumulate total capital gains of −118B, −28B, 16B, and 84B, respectively. After adjusting for the part of flows that is proportional to the group's initial capital weight, the bottom panel of Fig. 4 shows the corresponding cumulative adjusted-flow-generated gains for the four household groups: −104B, −15B, 23B, and 96B, respectively. In sum, about 40% of the total wealth redistribution (100B/250B) between the largest and smallest household groups is attributable to flows into and out of the market as a whole, while the remaining 60% to the heterogeneity in portfolio composition.[19]

For ease of comparison, Table 2 Panels A1 and A2 list all the aforementioned quantities of capital flows and flow-generated gains for the four household groups over various horizons. We further classify household accounts into two cat-

[19] Since we do not observe households' other investments, we are unable to calculate the benchmark return earned by households in other markets, so may over- or under-state households' gains from market timing.

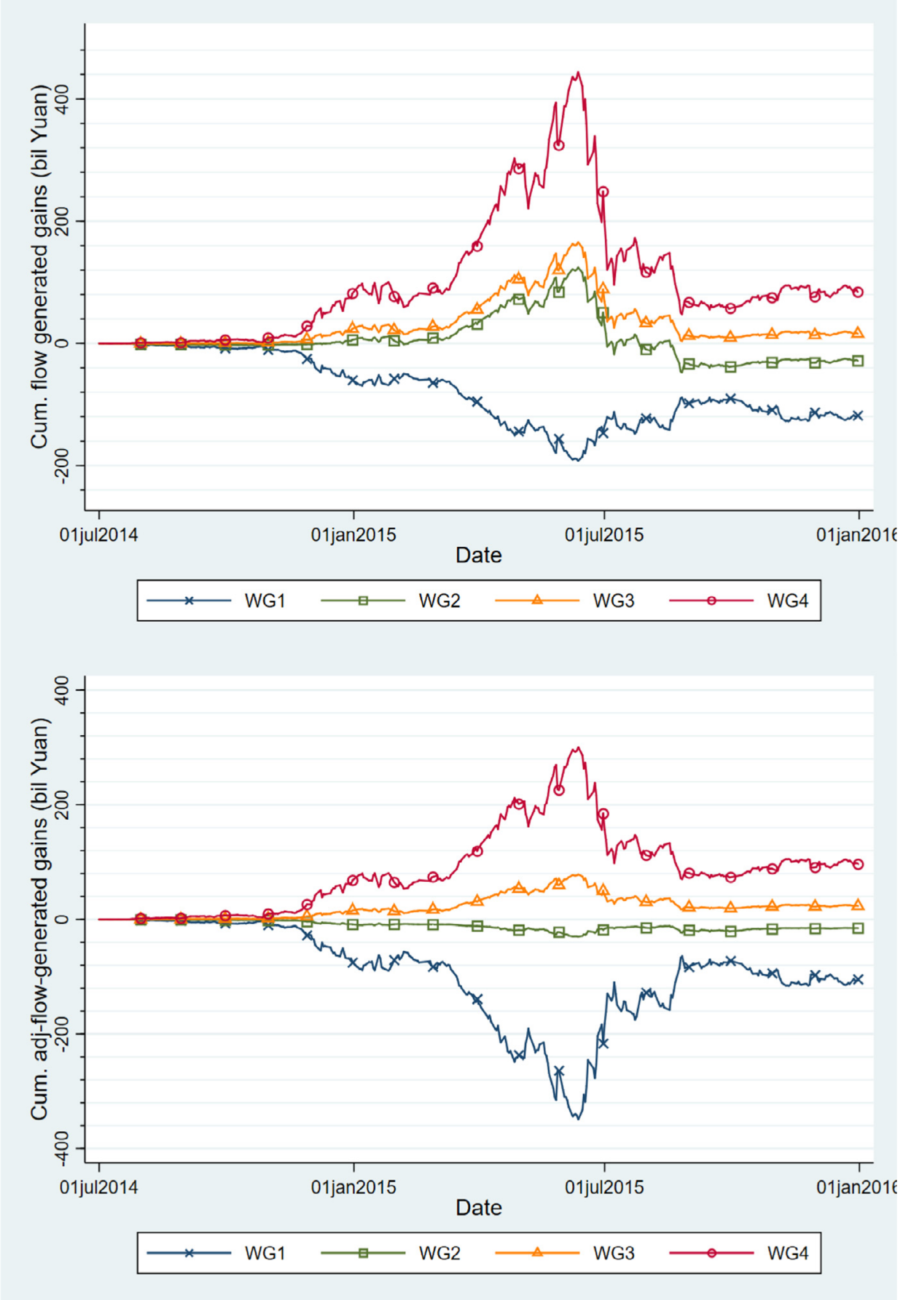

Fig. 4. Flow-Generated Gains at the Market Level in the Bubble-Crash Period. This figure shows cumulative flow-generated gains at the market level by different wealth groups in the household sector. The top figure shows flow-generated gains/losses, and the bottom figure shows adjusted-flow generated gains/losses. Households are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value), with cutoffs at RMB 500 K, 3 M, and 10 M. WG1 includes investors with account value less than 500 K, and WG4 includes investors with account value greater than 10 M. We calculate the market-level cumulative (adjusted-) flow-generated gains of each household group by multiplying its daily flows to the market with the subsequent market return (till the day in question), and then summing this up over all days till the day in question (see Eqs. (7) and (8)). Capital gains are in billions of RMB.

egories: those that exist at the start of our sample, and those that are opened during our sample; we label the former “existing accounts” and the latter “new entrants.” Online Appendix Table A2 shows the flow patterns and flow-generated gains of the two types separately. Two observations are worth pointing out. First, not surprisingly, existing accounts as a whole sell their equity holdings, while new entrants increase their equity holdings throughout this 18-month period. This is consistent with the recent finding that high market returns tend to draw new entrants to the stock market (e.g., Kaustia and Knüpfer, 2012). Second, existing accounts and new entrants exhibit one common pattern: within either category, relative to smaller accounts, larger accounts increase their risky equity holdings in the boom period and reduce their equity holdings in the bust period. Panel A2 further shows that existing accounts contribute roughly two thirds of the total wealth redistribution between the top 0.5% and bottom 85% of households, while new entrants contribute the remaining one third.

Table 2 Panel A3 shows wealth redistribution across households in a period of a relatively calm market, from January 2012 to December 2014. (The cumulative gains and losses to each household wealth group during this period are also plotted in Fig. 5.) As is clear from the table and the figure, the gains and losses to the four household wealth groups in the calm period are an order of magnitude smaller than those in the bubble-crash episode. For example, in any 18-month subperiod in the two-and-half years prior to June 2014, the ultrawealthy (those in the top 0.5% of the equity wealth distribution) have a gain of at most 8B (21B) RMB under the buy-and-hold (proportional-trading) benchmark. These figures amount to 1 and 3% of the initial equity wealth held by the top household group (compared to the 30% gain between July 2014 and December 2015). We observe losses of similar magnitudes experienced by the bottom household wealth group in this period.

In Panel B of Table 2, we report flows and flow-generated gains for the three investor sectors. Corporate investors had a collective outflow from the stock market of 126B RMB in the boom period and an inflow of 952B RMB in the bust period, and had a total trading gain of 113B RMB (75B by state-owned corporations). This is expected, as the “national team” went in near/at the bottom of the market to put a backstop on investors’ fire sales. Just like the Fed and the US Treasury that ended up registering a gain from their bailout programs in the Global Financial Crisis (e.g., Calomiris and Khan, 2015), the Chinese “national team” also made a profit by providing much-needed liquidity to constrained investors.

Institutional investors had a collective inflow of 78B RMB in the boom period and a further inflow of 138B in the bust period, and had a total gain of 252B RMB from trading. The household sector as a whole had an inflow to the market of 1142B RMB in the boom period, an outflow of 775B in the bust period, and a total trading gain of 6.7B RMB in this 18-month period. Appendix Fig. A2 plots the flow-generated gains of the three investor sectors.

The sum of the trading gains across the three investor sectors is over 370B RMB in this period. The reason that it is not zero is because trading by the three investor sectors does not always cancel out; instead, the aggregate flow of the three investor sectors is equal to the increase in tradable shares due to, for example, IPOs, SEOs, and conversions of non-tradable to tradable shares. In other words, these newly created shares experienced a total loss of 370B RMB in our sample.

5. Heterogeneity in investment skills

We have so far examined households’ stock market investment decisions during an extraordinary bubble-crash episode, and the resulting gains and losses. The findings are striking: the top 0.5% households gain, while the bottom 85% lose, over 250B RMB in the 18-month period, more than ten times that in calm periods. In this section, we provide evidence that our documented pattern of wealth redistribution is consistent with significant heterogeneity in investment skills across household groups. (In Section 2 of the Online Appendix, we entertain additional explanations for our findings through the lens of a simple, stylized portfolio-choice model.)

5.1. Investment skills at the market level

To formally examine which groups of investors are more (or less) skilled at predicting future market returns, we conduct a simple portfolio analysis. Specifically, we assume that a) every household group starts with 100% of financial wealth invested in the stock market (in other words, stock wealth equals the total financial wealth as of July 1, 2014), they then either borrow at the risk free rate to fund further investment into the stock market or save the proceeds in risk free assets from selling stocks ;[20] b) every RMB invested in or divested from the stock market tracks the market index. Assumption b) allows us to abstract away from stock selection. Assumption a) enables us to infer market-timing ability by regressing returns of the levered portfolio in the stock market on contemporaneous market returns; a positive (negative) alpha from the regression indicates positive (negative) timing ability.

The results are shown in Table 3. As can be seen from Panel A, there is a positive monotonic relation between initial equity wealth and market timing ability. For example, the bottom 85% of households have a significantly negative timing alpha of −2.1 bps per day (t-statistic = −5.24), while the top 0.5% have a positive alpha of 0.5 bps per day (albeit statistically insignificant). The difference of the two at 2.6 bps per day (t-statistic = 2.47) is both statistically and economically large: this implies a return differential of 6.5% a year, or nearly 10% over our 18-month period. There is also a positive monotonic relation between account value and average beta of the levered portfolio: the average portfolio beta of the bottom group is 0.94 and that of the top group is 1.19, with a difference of 0.25 (t-statistic = 21.90). Given a cumulative, capital-weighted market return of 40% in our sample, this beta differential implies a cumulative return difference of about 10%.[21] One possible explanation for why the wealthy have a larger stock market exposure than the poor in our sample (despite the fact that smaller accounts hold riskier stocks at the beginning of our sample) is that the wealthy are less capital constrained, so can

[20] For simplicity, we assume that the risk-free rate is zero; our results are virtually unchanged with other risk-free rates (e.g., 6%, 10%).

[21] Following Dichev (2007), when averaging market returns over different months, we weight each month by the total market value at the end of the previous month, to more accurately reflect the experience of the representative investor in the market.

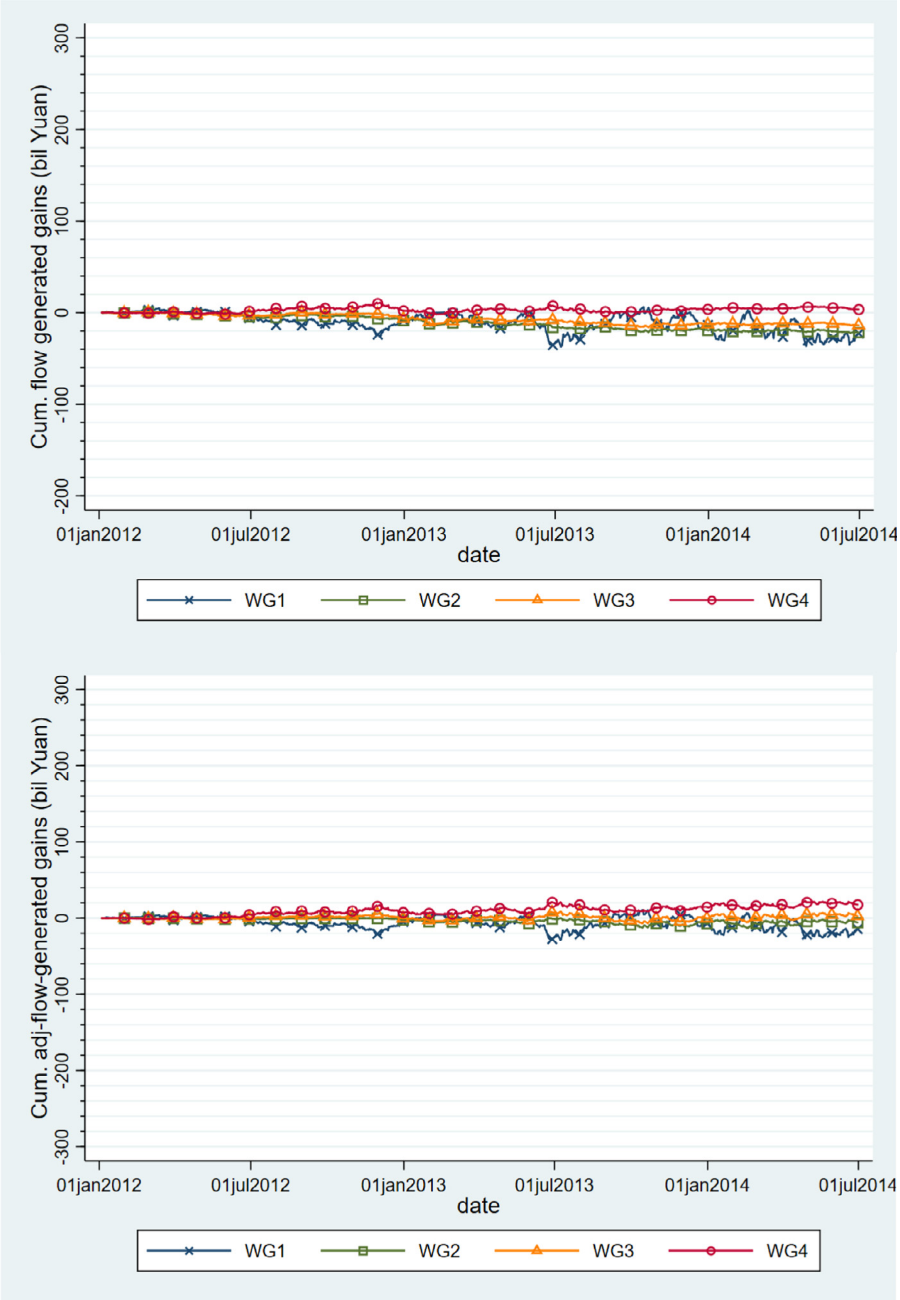

Fig. 5. Flow-Generated Gains of Households in Calm Market Conditions. This figure shows cumulative flow-generated gains by different wealth groups in the household sector for the period January 2012 to June 2014, during which the market is relatively calm. The top figure shows capital gains generated by the raw value of flows, and the bottom figure the adjusted flows (calculated using Eq. (3)). Households are classified into four groups based on their total account value at the end of December 2011 following the procedure described in Section 3. We calculate the cumulative (adjusted-) flow-generated gains of each household group by multiplying daily flows to a stock with the subsequent stock return (till the day in question), and then summing this up over all days till the day in question and across all stocks in the household portfolio (see Eqs. (5) and (6)). Capital gains are in billions of RMB.

more easily move capital into the stock market during the boom period. In sum, roughly half of the wealth redistribution at the market level can be explained by differences in timing ability and the other half by the wealthy's overall larger exposure to the stock market.

In Online Appendix Table A3, we classify all household accounts into those that exist before July 2014 and new entrants after July 2014. We again observe monotonic relations between portfolio alpha and account value, and between market beta and account value. One interesting observation is that for accounts that exist before July 2014, all wealth groups have

Table 3
Market Timing: A Portfolio Approach
This table reports regression results of daily returns to a levered portfolio in the stock market held by different household wealth groups on contemporaneous market returns. Specifically, the levered portfolio is constructed by assuming a) every household group starts with 100% invested in the stock market (i.e., stock wealth equals the total financial wealth as of July 1st, 2014) and then either borrow at the risk free rate to fund further investment into stocks or save the proceeds from selling stocks in risk free assets; b) every RMB invested in or divested from the stock market tracks the market index. Within the household sector, investors are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value); WG1 to WG4 include investors whose total account value fall into the brackets of <500K, 500K-3M, 3M-10M, and >10M, respectively. Panel A shows the results in our main sample of the bubble-crash period (201407 to 201512), and Panel B repeats the same exercise in the two-and-half years prior to our main sample (201201 to 201406), during which the market is relatively calm. T-statistics, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Bubble-crash period: 2014 Jul. - 2015 Dec.

	Levered portfolio return: $w_{stock}MktRet_t+(1-w_{stock})R_{f,t}$				
	WG1	WG2	WG3	WG4	WG4-WG1
$MktRet_t$	0.94202***	1.09820***	1.13438***	1.18630***	0.24429***
	[214.29]	[245.74]	[185.44]	[129.55]	[21.90]
Alpha	-0.00021***	-0.00018***	-0.00006	0.00005	0.00026**
	[-5.24]	[-3.75]	[-0.92]	[0.51]	[2.47]
No. Obs.	370	370	370	370	370
Adj. R^2	0.998	0.998	0.998	0.996	0.884

Panel B. Calm period: 2012 Jan. - 2014 Jun.

	Levered portfolio return: $w_{stock}MktRet_t+(1-w_{stock})R_{f,t}$				
	WG1	WG2	WG3	WG4	WG4-WG1
$MktRet_t$	1.42182***	1.00087***	0.97825***	0.95033***	-0.47149***
	[65.54]	[742.97]	[703.70]	[392.01]	[-21.19]
Alpha	-0.00002	-0.00001	-0.00001	-0.00001	0.00001
	[-0.20]	[-1.39]	[-1.29]	[-0.74]	[0.12]
No. Obs.	600	600	600	600	600
Adj. R^2	0.966	1.000	1.000	0.999	0.757

positive timing alpha; for example, existing accounts with an initial equity wealth above the 10 M RMB cutoff have a daily alpha of 2.3 bps (t-statistic = 1.74). In contrast, accounts that are opened during the boom-bust episode all have negative timing alpha (including the largest ones); for example, new entrants with initial equity wealth below 500 K RMB have a negative daily alpha of −7.9 bps (t-statistic = −3.40), or an annual alpha of −19.9%.

In Panel B of Table 3, we conduct the same return attribution exercise using data from the two-and-half years prior to June 2014, when the market is relatively calm. As can be seen from the panel, the portfolio timing alpha across all wealth groups in this calm period is indistinguishable from 0, and the difference in alpha between the top and bottom household groups of 0.1 bps (t-statistic = 0.12) is an order of magnitude smaller than that in Panel A (2.6 bps).

5.2. Investment skills at the stock level

We next turn to households' trading activity at the stock level. To start, we provide a summary of household trading as a function of observable stock characteristics. More specifically, we conduct Fama-MacBeth regressions of weekly capital flows to individual stocks by each household group on a set of stock characteristics: the market beta, firm size, 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.[22] The dependent variable—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.

The results are shown in Table A4. Panel A presents regression 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 −0.055 (t-statistic = −2.30) to 0.053 (t-statistic = 4.18), and the difference of 0.108 (t-statistic = 3.61) is highly statically significant. In other words, the wealthier groups tilt their holdings towards high-beta stocks, while the smaller groups move away from high-beta firms in the boom period. Interestingly, as shown in Panel

[22] 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 et al. (2021).

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.

Fig. A3 plots the time variation in average portfolio betas of the top and bottom household groups. To make the portfolio beta comparable across time, in each week, we subtract from each group's portfolio beta the wealth-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 aggressively reduce their market exposures shortly after the market peak. All the other three household groups exhibit the opposite trading pattern. For reference, we also plot the imputed leverage ratios of the top and bottom household groups (based on the exercise in Section 2 of the Online Appendix). Not surprisingly, there is a strong correlation between the imputed leverage ratio of the household group portfolio and the average beta of the stocks in the portfolio.

Before moving on to discuss the return predictability of household trading, we wish to highlight a few additional observations from Table A4—the relations between stock-level trading and other firm characteristics. First, during the boom period, largest households are net buyers of large-cap, value, and marginable stocks while smallest households are net sellers in all three; the differences in coefficients between groups one and four 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 stock returns (so bet on short-term reversal), while all the other three groups chase short-term stock returns. Since the short-term contrarian strategy performs well in our sample period, this partly explains why the top household group outperforms the other three groups.

5.2.1. Predicting stock returns in the cross-section

Our evidence in Section 4.2 already suggests that wealthier households are more skilled at stock selection than the less wealthy. Specifically, accounting for heterogeneity in portfolio composition more than doubles the magnitude of wealth redistribution between the bottom 85% and top 0.5% of households, compared to when we consider only gains and losses resulting from market-level flows.

A. Baseline Results

To formally examine investors' stock selection skills, we conduct Fama-MacBeth forecasting regressions of future stock returns on stock-specific capital flows by each of the four household groups, controlling for stock characteristics that are known to forecast stock returns. Panel A1 of Table 4 reports regression results with normalized capital flows from each household group as the only explanatory variables. The regression results show that capital flows by the bottom two household groups significantly and negatively predict stock returns in the following week (we obtain similar results using returns in the next month). Capital flows of the largest household group, on the other hand, significantly and positively forecast future stock returns.[23] Panel A2 repeats the exercise by further controlling for the set of stock characteristics in Table A4. Across all specifications, the magnitude of the coefficient on *Flow* is at most 15% smaller in Panel A2 compared to the corresponding estimate in Panel A1. In other words, wealthier households have better stock selection skills than the less wealthy over and beyond what is captured by observable firm characteristics.

We provide further evidence for the ultrawealthy's superior stock selection ability using a calendar-time portfolio approach—that is, to track the daily returns to the equity portfolio of each household group.[24] As shown in Panel B of Table 4, relative to the CAPM model, the bottom 85% of all households earn a daily alpha of −13.2 bps (t-statistic = −5.01) in our 18-month sample, while the top 0.5% earn a daily alpha of 6.8 bps (t-statistic = 2.75). The difference between the two of 20.0 bps (t-statistic = 4.75), or over 50% a year, is highly statistically significant and can account for the majority of the wealth redistribution documented in the previous section. Further controlling for the size and value factors in the Chinese market (following Liu et al., 2019), or using the DGTW adjustment (matching based on beta, size and the book-to-market ratio), has little impact on our result. Put differently, our documented wealth redistribution is not driven by households' differential exposures to common risk factors, but rather heterogeneity in their ability to forecast firm-specific returns.

In Appendix Table A5, we repeat the exercise of Table 4 Panel A to examine the return predictability of trading by institutional and corporate investors. As can be seen from the last two columns of both panels in Table A5, institutional investors' trading at the stock level is a strong and positive predictor of stock returns in the following week; in contrast, corporate investors' trading does not forecast future individual stock returns.

B. Calm vs. *Extreme Periods*

Table 5 repeats the exercise in Table 4 for three additional periods: October 2014 to December 2015 (the bubble-crash period, Panel A), July 2014 to October 2014 (the mild-rise period, Panel B), and January 2012 to June 2014 (the calm period, Panel C). As shown in Panel A, the return predictability of trading by the bottom household group (per standard deviation of flows) in the bubble-crash period is −0.484 (t-statistic = −4.80) and that by the top household group is 0.444

[23] 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.

[24] To be consistent with our earlier tests, we only consider positions that result from households' trading in our sample period—that is, to discard their initial holdings at the beginning of our sample.

Table 4

Return Predictability of Flows and Calendar-Time Portfolios

This table analyzes the return predictability of trading by different household wealth groups in the bubble-crash period. Panels A1 and A2 report Fama-MacBeth regression results where the dependent variable is the future one-week stock return. The main independent variable of interest, *Flow*, is calculated as the stock-level capital flow in a given week, scaled by the average portfolio value of that investor group at the beginning and end of the same week. For ease of comparison, we normalize *Flow* by its standard deviation for each investor group. Panel A1 shows univariate regression results, and Panel A2 further controls 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). Panel B shows risk-adjusted daily returns of the calendar-time portfolios held by different household wealth groups, with respect to the CAPM, Fama-French 3-factor model, as well as DGTW-adjusted returns (controlling for size, value, and beta). We only consider positions that result from households' trading in our sample period, therefore discarding their initial holdings. Within the household sector, investors are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value); WG1 to WG4 include investors whose total account value fall into the brackets of <500K, 500K-3M, 3M-10M, and >10M, respectively. T-statistics, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A1. Return predictability of flows: univariate FM regression

	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG4-WG1
Flow	-0.394***	-0.259***	-0.022	0.397***	0.791***
	[-4.40]	[-3.83]	[-0.28]	[5.45]	[8.18]
Adj. R^2	0.013	0.014	0.013	0.011	
No. Weeks	78	78	78	78	

Panel A2. Return predictability of flows: FM regression with controls

	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG4-WG1
Flow	-0.564***	-0.433***	-0.143***	0.338***	0.902***
	[-9.71]	[-8.98]	[-2.91]	[8.81]	[13.85]
Beta	-0.156	-0.147	-0.142	-0.147	0.008
	[-0.97]	[-0.91]	[-0.88]	[-0.90]	[0.98]
Size	-0.128	-0.112	-0.122	-0.141	-0.0132
	[-0.60]	[-0.53]	[-0.58]	[-0.64]	[-0.65]
BM	0.398	0.432	0.452	0.421	0.023
	[0.90]	[0.98]	[1.03]	[0.96]	[1.16]
Margin	-0.096	-0.097	-0.096	-0.096	0.00
	[-1.10]	[-1.10]	[-1.10]	[-1.11]	[-0.03]
Past Returns	Yes	Yes	Yes	Yes	
Adj. R^2	0.143	0.141	0.138	0.139	
No. Weeks	78	78	78	78	

Panel B: Calendar-time portfolios (daily ret)

	WG1	WG2	WG3	WG4	WG4-WG1
CAPM alpha	-0.132***	-0.087***	-0.021	0.068***	0.200***
	[-5.01]	[-3.17]	[-0.82]	[2.75]	[4.75]
FF3 alpha	-0.124***	-0.089***	-0.025	0.059**	0.183***
	[-4.69]	[-3.22]	[-1.00]	[2.47]	[4.43]
DGTW-adj ret	-0.049***	0.001	0.027	0.077***	0.126***
	[-3.07]	[0.03]	[1.09]	[4.09]	[6.62]

(*t*-statistic = 6.20), with a difference of 0.928 (*t*-statistic = 7.94). Panel B conducts the same exercise for the mild-rise period. The return predictability of trading, again per standard deviation of flows, by the bottom household group in this period is −0.222 (*t*-statistic = −4.45) and that by the top household group is 0.180 (*t*-statistic = 5.83), with a difference of 0.401 (*t*-statistic = 4.06). Panel C shows the result for the calm period. The return predictability of trading by the bottom household group in the calm period is −0.118 (*t*-statistic = −5.24) and that by the top household group is 0.075 (*t*-statistic = 3.69), with a difference of 0.193 (*t*-statistic = 6.35).

In other words, the difference in flow-return predictability between the top and bottom household wealth groups in the bubble-crash period is more than twice as large as that in the mild-rise period, and more than four times as large as that in the calm period. In untabulated results, we further control for a large set of stock characteristics and continue to observe a two-to-four times larger flow-return relation in the extreme price-movement period than in the relatively calm periods. These results are consistent with the notion that the impact of heterogeneity in stock selection ability on household

Table 5
Return Predictability of Flows in Calm vs. Volatile Periods
This table reports Fama-MacBeth return regressions where the dependent variable is the future one-week stock return. The main independent variable of interest, *Flow*, is calculated as the stock-level capital flow in a given week, scaled by the average portfolio value of that investor group at the beginning and end of the same week. For ease of comparison, we normalize *Flow* by its standard deviation for each investor group. Panel A shows the results for the more volatile period (20141027-20151231), Panel B shows the results for the mild-rise period (20140701-20141024), and Panel C shows the regression results for various household wealth groups in the two-and-half years prior to our main sample (201201-201406), during which the market is relatively calm. Within the household sector, investors are classified into four groups according to their total account value (equity holdings in both Shanghai and Shenzhen Stock Exchanges + cash value); WG1 to WG4 include investors whose total account value fall into the brackets of <500K, 500K-3M, 3M-10M, and >10M, respectively. T-statistics, shown in brackets, are computed based on standard errors with Newey-West adjustments of four lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Univariate FM regression: the more volatile period (2014 Oct-2015 Dec)

	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG4-WG1
Flow	-0.484***	-0.311***	-0.003	0.444***	0.928***
	[-4.80]	[-3.93]	[-0.03]	[6.20]	[7.94]
Adj. R^2	0.015	0.016	0.015	0.013	
No. Weeks	62	62	62	62	

Panel B. Univariate FM regression: the mild-rise period (2014 Jul-2014 Oct)

	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG4-WG1
Flow	-0.222***	-0.186***	-0.165***	0.180***	0.401***
	[-4.45]	[-4.47]	[-3.56]	[5.83]	[4.06]
Adj. R^2	0.005	0.006	0.004	0.003	
No. Weeks	16	16	16	16	

Panel C. Univariate FM regression: the calm period (2012 Jan-2014 Jun)

	Ret_{1w}				
	WG1	WG2	WG3	WG4	WG4-WG1
Flow	-0.118***	-0.124***	-0.081***	0.075***	0.193***
	[-5.24]	[-4.18]	[-3.34]	[3.69]	[6.35]
Adj. R^2	0.005	0.007	0.005	0.003	
No. Weeks	123	123	123	123	

wealth inequality is substantially amplified in periods when both market volatilities and trading volume are abnormally high.

C. Predicting earnings announcement returns

If the top 0.5% of households indeed have superior stock-selection ability, either because they enjoy privileged access to non-public signals or they have more accurate/precise interpretations of public information, we expect stronger return predictability when their private knowledge is made publicly known—such as around firms' quarterly earnings announcements. To this end, we repeat our analysis in Table 4 but now focus exclusively on quarterly earnings announcements. The announcement day return is defined as the cumulative return in a three-day window around the announcement day t. The main independent variable is the trading by each household group in the announcing firm in days t-7 to t-3. We also include in the regression a set of control variables that are known to forecast stock returns.

The results are shown in Online Appendix Table A6, where the dependent variable is the three-factor-adjusted earnings announcement day return. As can be seen from the table, trading by the bottom 85% households negatively predicts future earnings announcement day returns, while trading by the top 0.5% positively forecasts announcement day returns. Importantly, the economic effect of flows on *daily* returns is about 50% larger than that in Table 4. These results provide further support that the return differential documented in Tables 4 and 5 is unlikely a compensation for systematic risk exposures, but rather evidence of the ultrawealthy's superior stock selection ability relative to other market participants.

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 that of the Chinese stock market between July 2014 and December 2015, during which the market index rose more than

150% before crashing 40%. Our administrative data include daily trading and holdings of all accounts in the Shanghai Stock Exchange, enabling us to examine wealth redistribution across the entire investor population.

Our analyses reveal that the largest household accounts, those in the top 0.5% of the equity 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. Household accounts below the 85th percentile exhibit the exact opposite trading behavior. Over this 18-month period, the top 0.5% of households gain, while the bottom 85% lose, over 250B RMB, or about 30% of either group's initial account value. In stark comparison, the gains and losses experienced by the four household wealth groups are an order of magnitude smaller in the two-and-half years prior to June 2014, when the market is relatively calm. Through the lens of a stylized portfolio choice model, we show that this wealth redistribution is unlikely to be driven by investors' rebalancing or trend-chasing trades and is instead more a reflection of the heterogeneity in households' investment skills (and possibly capital constraints).

Our finding that the largest 0.5% households gain much more than the bottom 85% in a boom-bust episode has implications for policy makers. It is widely believed that greater stock market participation is a path to prosperity and equality, especially in developing nations, where financial literacy and market participation are generally low. However, if the poor, less financially sophisticated end up investing actively in financial markets that are prone to bubbles and crashes, such participation can be detrimental to their wealth. This is particularly concerning given the recent finding that salient early-year experiences can have long-lasting impact on individuals' economic decisions decades later. Consequently, while greater stock market participation can be welfare improving, it is crucial to emphasize that active investing may result in the exact opposite.

Declaration of Competing Interest

None.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jmoneco.2022.01.001.

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