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**Abstract**

Due to their complex features, structured financial products can hurt the average investor. Are certain investors particularly vulnerable? Using account-level transaction data of retail structured funds, we show that the rich (sophisticated) benefit from complexity at the expense of the poor (naive). The poor-to-rich wealth transfer that results from trading structured funds is substantially greater than from trading simple, nonstructured funds. In an event study, we further confirm that part of this wealth transfer can be directly attributed to investors' differing responses to complexity. In particular, when a market crash triggers funds into a restructuring process and their prices are expected to shrink by half on a given day, the poor and naive subset of investors fails to respond effectively.

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# 1 Introduction

The market for structured financial products has experienced tremendous growth in Europe and is quickly expanding into US and Asian markets.[1] Traditional finance theory suggests that structured financial products are designed for risk-sharing purposes (Allen et al. 1994; Duffie and Rahi 1995). Recent literature, however, suggests a less benevolent motive: these products cater to naive investors, exploiting their behavioral biases and investment mistakes (Bordalo et al. 2016). Consistent with this motive, issuers advertise structured financial products with the upsides salient in headlines, but shroud the risks and management fees in complexity (Célérier and Vallée 2017). Obfuscated by complexity, retail investors end up earning negative risk-adjusted returns due to the high fees charged by banks and brokers (Henderson and Pearson 2011; Vokata 2018).

While there is growing evidence that investors, on average, are worse off from investing in complex financial products, there is reason to suspect that the effect is heterogeneous across investors. One reason relates to equilibria in consumer markets. In these markets, a firm exploits the naivety of certain consumers by shrouding its product's negative attributes. While these policies can successfully extract rents from naive consumers, they also allow the more sophisticated consumers to, in turn, exploit the firm (DellaVigna and Malmendier 2004; Gabaix and Laibson 2006). To see the intuition, consider an example from the hotel industry: Hotels are able to lower their room rates by upcharging add-ons such as valet parking and mini-bars. Overall, this results in a more expensive stay for naive consumers who do not understand the true cost, but a cheaper one for savvy consumers who know how to avoid costly add-ons; for example, by taking Ubers instead of paying for costly parking (Gabaix and Laibson 2006).

We argue that a similar mechanism applies when retail investors trade complex financial products. When a new product with both an upside and a downside is introduced to the market, issuers are incentivized to make the upside salient and shroud the downside. As a result, while all investors are equally informed about the upside, only the sophisticated ones know about the downside and are capable of managing the associated risks. Suppose that investors of different levels of so-

[1] Structured financial products are financial products whose payoffs vary nonlinearly with some underlying assets. According to Célérier and Vallée (2017), while the European retail market for structured financial products only dates back to the early 2000s, its size grew to 770 billion euros in 2012, almost 3% of all European financial savings. In the US, over $100 billion in yield enhancement products—one particular type of retail structured product—has been sold to households since the financial crisis and retail structured product assets under management exceeded $400 billion in 2015 (Célérier and Vallée 2017; Vokata 2018).

phistication begin trading this product on the secondary market and then, under certain market conditions, the downside risk rises but the price remains high. Sophisticated investors, seeing that the product is now overpriced, will choose to sell while the naive ones, unaware of the downside risk, choose to hold or even buy more.[2] In this case, complexity hurts the naive by subjecting them to risks they are not aware of and worsening their investment performance. Moreover, to the extent that sophistication is positively correlated with wealth, complexity further induces a wealth transfer from the poor to the rich.[3]

In this paper, we empirically establish this intuition by showing how making financial products more complex benefits the rich (sophisticated) at the expense of the poor (naive). This task is challenging for at least three reasons. First, many types of structured products are sold directly to investors by brokers, who, in their marketing scheme, disproportionally target naive investors (Vokata 2018; Egan 2019; Henderson et al. 2020). We aim to show that, even in the absence of broker activities, complexity itself can still harm naive investors. Second, detailed transaction data for retail structured products are hard to acquire; it is even harder to make comparisons with simpler products such as exchange-traded funds (ETFs). Third, even if one is able to demonstrate a significant wealth transfer induced by a particular structured product, the other features of this product could make it difficult to isolate the effect of complexity.

We design our empirical strategy to directly address all three concerns. First, we consider Chinese retail structured funds, which are issued by mutual funds and traded on the exchange. The exchange-traded setting gives equal access to all investors and leaves little space for aggressive sales tactics that target a particular subgroup. Second, we obtain the complete transaction records of all exchange-traded products, including both structured funds and other assets such as stocks and ETFs, for almost three million retail investors. This makes it possible to study the wealth consequences of retail structured funds and make appropriate comparisons with other (simpler) financial products. Third, we zoom into the 2015 Chinese market crash, which triggered a hidden,

[2] It may be worthwhile to put the two examples side by side. In the example of the hotel industry, asymmetry arises in the types of goods consumed: while both naive and sophisticated consumers take advantage of the cheap room rate, naive consumers also pay for overpriced add-ons, resulting in different total stay costs. In the example of complex financial products, asymmetry arises in the timing of ownership: while both naive and sophisticated investors trade at the same price at a given time, naive investors hold the asset when it is overpriced and sophisticated ones hold it when it is underpriced.

[3] For simplicity, we oppose "poor" to "rich," but it is not to be understood that we are referring to investors living in poverty. By "rich," we mean investors with a wealth above a high threshold; and by "poor," we mean not rich.

complex feature of retailed structured funds: due to a sharp drop in net asset value, many funds were forced into a restructuring process, after which fund prices were expected to automatically shrink by half. These restructuring events allow us to conduct an event study to examine how various investor groups respond to complexity. In doing so, we are able to place a lower bound on the size of wealth transfer directly induced by this complex feature.

More specifically, we study Chinese AB funds, a structured product similar to the primes and scores introduced to the US market in the 1980s (Jarrow and O'Hara 1989), and to mortgage-based securities (MBSs), which were popular instruments prior to the financial crisis of 2007-2008 (Ghent et al. 2017). AB funds are designed by slicing the payoffs of regular funds, often linked to an equity index, into two tranches: a fixed-income tranche, called A funds, and a levered-equity tranche, called B funds. In essence, B investors finance their position by borrowing from A investors at a fixed dividend (interest) rate.

For Chinese retail investors, the majority of whom cannot borrow money from their brokers, B funds possess a unique advantage: they provide cheap and easily accessible leverage. This feature, fueled by the 2015 Chinese stock market run-up, made B funds immensely popular. When the stock market peaked in June 2015, about 130,000 investors in our sample—or 11% of the active investor population—were trading B funds in that single month. While B funds are often advertised as providing "cheap leverage," there is also a hidden *downside*: B funds can experience a sudden and substantial drop in value due to two complex features, time-varying leverage and restructuring clauses, which we explain in greater detail in our third set of results below.

Our first set of results shows how the returns from trading B funds are distributed in the investor population. From 2014 to 2015, while the average investor approximately broke even, there was significant variation across wealth levels: the largest 1% of investors gained 500 million RMB while the remaining 99% lost 500 million RMB, implying a total wealth transfer of 1 billion RMB from the poor to the rich.[4] We find similar effects when we compare cumulative return rates. There was a similar wealth transfer from the naive to the sophisticated: 400 million RMB from the low-financial-literacy group to the high-financial-literacy group and 500 million RMB from the non-college-educated group to the college-educated group. These numbers, when applied to the

[4]Throughout the paper, we measure the wealth transfer across different investor groups by their difference in total RMB returns. This measure is based on the counterfactual that all investor groups—assuming an equal level of investment—receive the same rate of return from their investment.

entire investor population, suggest a total wealth transfer of 8 to 20 billion RMB from the poor and naive subset to the rich and sophisticated subset.

To further highlight the role of complexity in explaining these wealth transfers, our second set of results compares the effects of structured funds on wealth redistribution to those of nonstructured funds—namely ETFs. B funds and ETFs are often designed to trace the same index, which means that the underlying assets they hold are very similar. However, we find little evidence of a wealth transfer from the poor (naive) to the rich (sophisticated) via ETF trades. In fact, the bottom 99% of investors made slightly higher profits than the top 1% investors due to a greater initial investment and the two groups were very similar in their overall return rates. We also find little evidence of a wealth transfer across other dimensions, such as financial literacy.

In our third set of results, we directly show how complexity plays a role: in an event study, we show that structured funds redistribute wealth among investors due to investors' differing responses to complexity. To facilitate our empirical strategy, we first document three stylized facts about B funds: on average, they trade at a premium (that is, at a price higher than the NAV); this premium is time-varying; and its time-series variation closely follows the embedded leverage ratio.[5] Indeed, both in the time-series and in the cross-section, most of the variation in B's premium is explained by leverage. As a result, if leverage were to experience a sudden drop (for example, a reset), one should immediately expect the premium to shrink.

While most of the variation in leverage is endogenously determined by market fluctuations, a hidden restructuring clause can reset leverage *by force* when B's value drops below a prespecified threshold. This restructuring clause redistributes payoffs between the two tranches to ensure that the A tranche is risk-free; the threshold is typically set at such a low level that resets should rarely occur. However, the 2015 stock market crash triggered almost half of the B funds into a restructuring process. Right before restructuring, these funds had an average leverage ratio of 4:1 and were trading at a 100% premium. After the leverage resets, the premium dropped to essentially zero and the fund price fell by 50%. In other words, without taking any actions, investors would find the value of their B fund positions halved in just one day. Given the straightforward implications of restructuring events, the right course of action was well defined: as the NAV approached the

[5]The closed-end fund puzzle also considers a set of exchange-traded funds in which price deviates from the NAV and the premium (discount) is time-varying due to changes in investor sentiment (Lee et al. 1991).

threshold, investors should start pulling money out from B funds to avoid getting hit by a restructuring event. In fact, even after a restructuring event was triggered, trading would continue for one more day and investors had extra time to act accordingly.

Strikingly, most investors failed to trade in the right direction during these restructuring events: on average, they *increased* their holdings in B funds by almost 15% in the 11-day window before restructuring was triggered. In addition to losing 600 million RMB during this 11-day window, they lost another 400 million RMB after restructuring became effective. However, a small set of rich, sophisticated investors handled these events much better: they gradually pulled money out from B funds or kept their positions relatively intact. As a result, when restructuring eventually took place, they were largely shielded from the negative impact on their wealth. Indeed, we show that 250 to 450 million RMB of the wealth transfer can be directly explained by investors' different responses to restructuring events. We argue that rich investors were better traders during these episodes, because they understood the financial contract better. We discuss a host of alternative explanations based on liquidity provision, liquidity shocks, the reluctance to realize losses, and inattention and we show that they cannot account for the observed heterogeneity in returns and trading flows.

We run additional analyses to provide greater insight. First, while ignoring restructuring events could explain a lack of response, why did investors increase their positions prior to restructuring? We show that gambling preferences and borrowing constraints contributed to this increase in holdings. Second, were issuers aware of these restructuring risks *ex-ante*? By examining their initial prospectuses, we argue that issuers were largely aware of these risks but chose to "shroud" them in extremely lengthy documents. Finally, if retail investors were buying prior to restructuring, who was selling? We provide evidence that institutional investors were on the other side of the trade and were able to pull out before restructuring took place.

The three sets of results above show that naive and poor investors are particularly vulnerable when trading complex securities such as structured funds. What triggers them to buy these products in the first place? In our last set of results, we show that investors bought B funds because of the high returns they delivered during the market boom. In particular, most of the entries happened after the market experienced a large positive return in the previous month. The majority of B investors were extrapolators who tended to buy stocks that had had positive returns in the past.

Therefore, consistent with Bordalo et al. (2016), naive investors were attracted by the high "headline" returns delivered by B funds during the market boom, but ignored the negative consequences that could result from the funds' complex features during a crash.

Our paper contributes to a recent literature that empirically and theoretically examines the welfare implications of retail structured products (Henderson and Pearson 2011; Chang et al. 2015; Célérier and Vallée 2017; Kondor and Koszegi 2017; Vokata 2018). A key result in these earlier papers is that investing in retail structured products is suboptimal and can make the average investor worse off. Instead of studying average effects, we focus on heterogeneous effects and redistributional consequences. In particular, we show how complex features of a security contribute to a substantial cross-subsidization from poor naive investors to rich sophisticated ones.[6] Our paper thus speaks to the welfare implications of salience and inattention (Bordalo et al. 2012, 2013; Gabaix 2014; Bordalo et al. 2016). In our setting, structured funds provide cheap leverage, an attribute that is made all the more salient by a booming market. However, investors largely ignore the product's other attributes, resulting in a substantial financial loss.

Broadly, our paper also contributes to a growing literature on wealth inequality.[7] The distribution of returns on wealth is a key ingredient in quantitative models that aim to understand wealth inequality (Huggett et al. 2011; Benhabib et al. 2017, 2019). Earlier work suggests that returns are similar across wealth buckets (Saez and Zucman 2016), but recent work offers evidence that returns increase with wealth (e.g., Fagereng et al. 2016, 2020). To understand the sources of return heterogeneity, prior literature has proposed skill-based explanations based on market timing, stock picking, and awareness of the need to diversify (An et al. 2019; Campbell et al. 2019; Fagereng et al. 2020). In this paper, we propose a new explanation in the form of a "complexity tax." Given the asymmetry between the poor and rich in their levels of financial sophistication, making securities more complex effectively taxes the poor and subsidizes the rich. This complements a new literature that highlights the importance of behavioral biases in explaining wealth inequality (Epper et al. 2020).

In the context of Chinese markets, a number of other papers have used the introduction of war-

[6]A vast literature studies how naive investors make mistakes and earn poor returns (see Barber and Odean (2013) for a recent review). Our analysis differs from previous studies in showing that, in the presence of both sophisticated and naive investors, adding complexity to these standard products makes this asymmetry much greater.

[7]See Benhabib and Bisin (2018) for a review of this literature.

rants between 2005 and 2008 to study the welfare implications of complex securities (Xiong and Yu 2011; Pearson et al. 2020; Li et al. 2020). Among these papers, the closest to ours is Li et al. (2020): they document that trading performance is heterogenous among warrant traders and attribute the outperformance of large traders to their market-making activities. Our paper is different in three aspects. First and foremost, the mechanism for generating performance heterogeneity is different. In our setting, large investors perform better because they understand complexity better and are able to trade appropriately when downside risk changes; we find no evidence of market-making contributing to their outperformance. Second, the setting of structured funds is distinct, not only in that they represent a nascent asset class, but also because they allow for a direct comparison with ETFs, which teases out the effects of "structuring." Third, our analysis is more of a quantitative nature: we not only demonstrate the magnitude of the wealth transfer, but also are able to directly quantify the effect of complexity through an event study.

Finally, our results offer a cautionary tale to policymakers about the unintended consequences of financial innovation. While the introduction of new, complex products in theory should help complete the market and improve investor welfare, these products may create extra room for speculation.[8] In the case of Chinese restructured funds, the introduction of B funds nicely filled the gap of leverage products and the inclusion of the restructuring clause seemed well-reasoned and innocuous *ex-ante*. However, once introduced, they were largely used by small naive investors to make speculative trades without knowing much about the product itself. This complements a recent literature that studies complex financial products through the lens of advisor conduct (Egan 2019; Egan et al. 2019; Bhattacharya et al. 2020). Our analysis uses an exchange-traded setting to demonstrate that complex financial products could hurt naive investors due solely to their product design. We therefore hope our results motivate future work on alleviating the downsides of financial innovation. For example, if a higher barrier to entry had been imposed and better guidance had been provided to the less-informed investors, they could have navigated through the market fluctuations better and made wiser investment decisions.[9]

[8]In the US, the pool of exchange-traded assets has expanded dramatically and some of these assets, such as leveraged ETNs and inverse ETFs, are quite complex. Moreover, popular trading apps like Robinhood make them more accessible to retail investors. Despite this popularity, there is little evidence that these products are welfare-improving for retail investors. For instance, during the COVID-19 pandemic, leveraged ETNs anecdotally contributed to personal bankruptcies ("Individual Investors Get Burned by Collapse of Complex Securities," *The Wall Street Journal*, June 1, 2020).

[9]Following this episode, the Chinese regulators halted the issuance of new structured funds and placed a higher

There are some limitations to note about our analysis. First, because there is a wide range of structured financial products and we only study one type, our results should be applied to other settings with caution. For products that are more complex than retail structured funds, we conjecture—but do not show—that the scale of the associated wealth transfer could be greater. Second, despite the popularity of B funds, they are a small fraction of the entire market. Although their impact on returns was large conditional on participation, the overall impact on the average investor was small. However, if the introduction of one particular product has already had such a large impact on investor welfare, we suspect that the introduction of other products, such as warrants and index futures, may have had a similar effect.

The rest of the paper proceeds as follows. Section 2 introduces the institutional background and data sources. Section 3 studies the wealth consequences of B funds and makes comparisons with ETFs. Section 4 examines investors' trading behaviors and returns during restructuring events. Section 5 seeks to understand the entry decisions into B funds. Section 6 concludes.

# 2 Institutional Background and Data

## 2.1 Overview of AB funds

Financial Industry Regulatory Authority (FINRA) Notice to Members 05-59 defines structured security products as "securities derived from or based on a single security, a basket of securities, an index, a commodity, a debt issuance and/or foreign security" (SEC 2011). According to this definition, AB funds are a particular type of structured product: they are designed by slicing the payoffs of a regular mutual fund (parent), which are often linked to a bond or equity index, into two tranches, a dividend-based tranche (A tranche) and an appreciation-based tranche (B tranche). Shares are then issued for each tranche with the initial net asset value (NAV) normalized to one per share. The A tranche receives interest payments according to a prespecified interest rate, which means that its NAV is well defined and not affected by price fluctuations in the underlying assets. The B tranche has the residual claim and is very sensitive to price movement in the underlying assets. Essentially, B investors take a levered position in the underlying assets by borrowing from

barrier to entry, largely due the negative consequences documented in this paper.

A investors at the interest rate.

Like a standard mutual fund, the parent fund can have its shares created or redeemed at the NAV through the brokers; it is typically *not* traded on the exchange.[10] In contrast, A and B shares are traded on the exchange and cannot be directly created or redeemed at the brokers. As a result, the standard arbitrage mechanism through creation and redemption is not at work.[11] Instead, the main arbitrage mechanism—the so-called "create-split-sell" trade—involves the conversion of shares between the parent fund and the two tranches. For example, suppose that both A and B are trading at a premium. To trade on this premium, the arbitrageur would need to first create new parent shares through the broker, then split these shares into A and B shares, before she can finally sell them on the exchange; a reverse trade can be designed when A and B are trading at a discount.

There are two significant limitations to this arbitrage mechanism. First, each of the three steps in the "create-split-sell" trade is subject to various trading rules and the entire process takes at least two days. Such an arbitrage trade is therefore subject to various risks, especially when the market is volatile (Shleifer and Vishny 1997). Second, while the mechanism can prevent the *combined* price of the two tranches from deviating too much from the parent fund's value, it does *not* ensure that each tranche by itself is correctly priced. For example, if A is trading at a discount and B is trading at a premium, but the combined price of A and B equals the value of the parent, the "create-split-sell" trade does not make money. In our data, these arbitrage trades are rare, and the number of shares outstanding is relatively stable on the secondary market. B funds can therefore be conveniently thought of as levered closed-end funds.

As we show below, trading from retail investors concentrated on the equity-linked B tranche, to which the bulk of our subsequent analysis is devoted. 115 equity-linked B funds were traded on the exchange by the end of 2015. A brief summary of their characteristics can be found in Table 1. About a third of these funds are index funds and the other two-thirds focus on a particular industry or investment style. B investors pay A investors a similar rate 3 to 4% above the one-year fixed deposit rate (around 3% in 2015). Most funds have an initial leverage of 1:1. They also adopt a

[10]For over a dozen funds, the parent fund is listed on the Shanghai Stock Exchange and can be traded on the secondary market. The main exchange for structured funds, the Shenzhen Stock Exchange, prohibits funds from listing on the secondary market.

[11]For instance, if an ETF is trading at a price higher than its NAV, arbitrageurs can trade away such mispricing by buying the underlying securities, creating new ETF shares, and selling them on the market. A reverse trade applies when the ETF is trading at a discount.

similar NAV threshold of 0.25 as the trigger for restructuring events, which we explain in greater detail below.

### 2.1.1 Complex features

While B funds are similar in spirit to levered closed-end funds, two additional features make them more *complex*: time-varying leverage and restructuring clauses. Throughout the paper, when we refer to the complexity of retail structured funds, we specifically refer to these two features.

**Time-varying leverage.** Unlike a standard levered fund, which is balanced daily to maintain a constant leverage ratio, B's leverage ratio is time-varying. Below, we use a simple example to illustrate this feature. Suppose that with a total NAV of 200, parent fund P issues 100 shares of A and 100 shares of B, all with a per-share NAV of 1. Assume an annual interest rate of 8% that makes payments quarterly. Table 2 shows how changes in P's NAV correspond to changes in NAV for A and B. When P rises in value, B also rises in value, reducing leverage; similarly, when P drops in value, B also drops in value, increasing leverage. This feature of time-varying leverage poses a first layer of complexity from the point of view of risk management. For instance, to keep leverage at a constant level, investors need to balance their portfolios on their own on rather than delegate the task to fund managers.

| Time | $NAV_P$ | $NAV_A$ | $NAV_B$ | Leverage ($NAV_B/NAV_A$) |
|---|---|---|---|---|
| Month 3 | 1.1 | 1.02 | 1.18 | 0.86 |
| Month 6 | 1.3 | 1.04 | 1.56 | 0.66 |
| Month 9 | 0.8 | 1.06 | 0.54 | 1.96 |
| Month 12 | 0.65 | 1.08 | 0.22 | 4.91 |

Table 2: An example of AB fund payoffs

**Restructuring clauses.** A second layer of complexity comes from the restructuring clauses in place to reset leverage when it becomes too large. Notice that, without putting in any extra clauses, the A tranche is not risk-free: if the parent's NAV drops by around 50%, it will start to eat into the payoffs of A investors. In fact, in Table 2, when P's per-share NAV drops to 0.65 in month 12, the embedded leverage already rises to 4.91 and the A tranche is on the edge of being affected. To avoid such scenarios and ensures that the A tranche is risk-free, once the per-share NAV of B falls below a certain threshold, it automatically triggers a restructuring process.[12] As shown in Table 1, this threshold is typically set at 0.25, which corresponds to a substantial drop of 75% from the initial B fund value.

During the restructuring process, the number of shares is cut short for both tranches so that their per-share NAVs are normalized to 1. For example, in Table 2, when the per-share NAV of P falls to 0.65 and triggers the restructuring process, the number of B shares will be reduced from 100 to 22 ($= 0.22 \times 100$) so that the per-share NAV is reset to 1. To adjust the leverage ratio back to 1:1, the number of A shares will also be reduced to 22, and the residual NAV ($1.08 \times 100 - 1 \times 22 = 86$) will be converted back into 86 shares of P. Therefore, after restructuring, A investors would receive both a smaller number of new A shares and extra shares of the parent fund; the latter can be immediately cashed out at the broker. We explain the timeline of restructuring events in greater detail in Section 4.

### 2.1.2 Other structured products

In the US market, similar structured products, called primes and scores, were introduced in the 1980s and exhibited significant mispricing from the underlying assets (Jarrow and O'Hara 1989). More recently, researchers have looked into other complex financial products and their wealth consequences: retail structured products in Europe (Célérier and Vallée, 2017), yield-enhancement products in the US (Henderson and Pearson 2011; Vokata 2018), and private-label mortgage-backed securities before the financial crisis (Ghent et al. 2017).

All these products have complex features that are not easy to understand for a typical household, but the nature of complexity varies from one product to another. Specifically, retail structured products in Europe on average have 2.5 features in their payoff formula (Célérier and Vallée 2017); yield-enhancement products in the US have yields that are tied to the performance of other products like equities (Vokata 2018); private-label mortgage-backed securities have complicated waterfall

[12] A similar restructuring process is triggered when the per-share NAV of the parent fund rises above a certain threshold (1.5 or 2 RMB for most funds). However, this happens rather infrequently and the wealth implications of such events are much less significant.

structures (Ghent et al. 2017). In our setting, structured funds are made complex by the embedded time-varying leverage and various restructuring clauses.

We note a significant distinction of our setting from those of previous studies, which mostly analyze illiquid financial products at issuance. Due to sellers' market power and screening mechanism, these products are likely to be sold to less-sophisticated investors over the counter. Indeed, Egan (2019) finds that brokers target unsophisticated investors to sell yield-enhancing products. In our paper, we consider an exchange-traded product that is not directly sold to investors by brokers; rather, all investors have equal access to it. This allows us to highlight a previously ignored channel: even without brokers screening in desired investors, complexity may still hurt naive investors more than others due to the initial product design.

## 2.2 B Funds during the bubble

AB funds—especially B funds—became immensely popular during the 2015 Chinese stock market boom. Sub-figure 1a compares the popularity of AB funds and warrants, which were introduced in 2006 and led to a trading frenzy (Xiong and Yu 2011). By June 2015, when the stock market reached its peak, almost 100,000 investors were holding B funds in their month-end portfolios. Overall, more than 140,000 investors have traded B funds between 2014 and 2015. These two numbers roughly represent 8.6% and 12.0% of the active investor population in our sample. Compared to warrants, B funds exhibited a similar, if not greater, popularity in terms of number of participants. A funds were much less popular: even at the peak, only around 8,000 investors were trading them.

### 2.2.1 Market size

A key exercise we perform is to study the wealth consequences of structured funds. For a financial product to have a significant impact on a household's financial wealth, it should at least account for a sizable fraction of the investor's asset portfolio. Sub-figure 1b shows the market size of AB funds and ETFs. Prior to 2015, the market for AB funds grew steadily, but was, on average, much smaller than the market for ETFs. However, during the 2015 stock market boom, due to the issuance of many new funds, AB funds' total assets under management (AUM) reached 350 billion

RMB—almost 10% of the entire mutual fund industry—and was comparable in scale to the ETF market.[13]

Table 3 shows the monthly distribution of B funds' portfolio weight in an investor's equity account conditional on having a positive balance of B shares. For an average (median) investor in a given month, B funds constituted 32% (14%) of her equity holding, which includes all exchange-traded equity products such as individual stocks and ETFs.[14] In fact, more than 10% of B investors were holding only B funds in their equity accounts. Therefore, consistent with some recent empirical work (Calvet et al. 2020), the leveraged B funds appeared to be encouraging households who were otherwise reluctant to take risks to start investing in risky assets. While only 10% of the investors were investing in this asset class, the conditional stake was rather high. For most of these retail investors, B funds were the most complex assets in their accounts.

### 2.2.2 Complex features

**Time-varying leverage.** Retail investors in the Chinese stock market were highly subject to leverage constraints (Bian et al. 2018a,b). When the market experienced a sharp rise in stock prices, return-seeking investors were searching for alternative ways borrow money and B funds precisely filled this gap. First, opening a regular leverage account required a minimum account balance of 500,000 RMB for at least 20 trading days and 6 months of prior trading experience, but trading B funds imposed no such requirements. Second, the embedded interest rate was just 3% to 4% above the one-year fixed deposit rate, which was cheaper than or comparable to the rates charged by brokers and shadow leverage firms.[15] Third, the exchange-traded feature made B funds highly liquid and easily accessible to small retail investors.

As a result of this "cheap leverage" feature, B funds became exceedingly overpriced in 2015.[16] Figure 2 plots the time-series of their average leverage and premium in 2015. During the first few months of 2015, B's leverage gradually dropped due to the rising market and the associated

[13] See Figure A.1 in the Appendix for more details. Overall, the issuance of structured funds was steady until the first half of 2015, when a disproportionally large number of structured funds was issued.

[14] We do not observe their mutual fund holdings other than ETFs. However, according to An et al. (2019), the fraction of the stock market held by mutual funds was very small (less than 5%) during this period.

[15] In 2015, the average interest rate charged by brokers for providing leverage was between 8% and 9%. In comparison, the average interest rate paid to A funds was between 6% and 7%—substantially lower. To be more precise, B fund investors also have to pay management fees, which were typically around 1% annually.

[16] By overpriced (underpriced), we mean trading at a price higher (lower) than the NAV.

premium also declined slightly. When the market crashed in June, leverage almost doubled and B funds were trading at an average premium of 30%. Importantly, B's leverage and premium moved closely with each other in time-series, with a correlation coefficient of 0.52. This high correlation suggests that, consistent with leverage constraints, the high premium during the crash was largely driven by a demand for leverage. In the Appendix, we show that a similar relationship holds in the cross-section: funds with a higher leverage were associated with a higher premium.[17] Overall, it is clear that most of the variation in the B premium was driven by the embedded leverage.

If the B premium was so large, what prevented the arbitrageurs from correcting this mispricing? There were significant limits to arbitrage, as discussed in Section 2.1. Because investors cannot directly create new shares of B on the secondary market, they need to create new parent shares first and split them into A and B shares for selling on the secondary market. However, A shares were trading at a large discount: as Figure 2 shows, when B funds were trading at a large premium, A funds were typically trading at a deep discount. As a result, while the combined price of A and B shares remained close to the fundamental value, both A and B were substantially "mispriced".[18]

**Restructuring events.** Again, to ensure the dividend-like feature of the A tranche, B funds had restructuring clauses to reset leverage when the value of the underlying assets drop below a certain threshold. While the threshold was set at such a low value that restructuring events should occur rather infrequently in normal market conditions, the 2015 market crash triggered 52 funds—almost half of the funds we study—into a restructuring process.[19] Many funds were forced to reset their leverage back to 1, and the associated premium vanished afterwards. The disappearance of the B premium led to important implications for investor welfare, as investors holding B funds during restructuring would find the value of their B positions halved. Therefore, these events allow us to conduct an event study to examine how investors respond to complexity differently and how these differing responses lead to wealth redistribution. We return to these restructuring events in Section 4.

[17] In a nutshell, we run a series of panel regressions with different specifications of fixed effects (fund and time); the resulting R-squared ranges from 0.56 to 0.84. We present more detailed evidence about the relationship between leverage and premium in the Appendix.

[18] We include additional analysis of the limits to arbitrage in the Appendix.

[19] In the Appendix, Figure A.4 plots the distribution of all restructuring events from 2014 to 2018 and shows that most are concentrated in the 2015 market crash.

## 2.3 Data

We use two main datasets, both from a large national brokerage in China, in our empirical analysis. The company has branches in almost all of China's provincial districts and is a market leader in several regions. Moreover, it provides comprehensive capital market services, making all exchange-listed securities available to its clients. This enables us to observe the trading records of all exchange-listed assets; namely, stocks, warrants, equity and bond ETFs, and various listed funds.

The first dataset is the complete retail trading history for all exchange-traded products from 2006 to 2016. In particular, we focus on the trading records for three types of asset: AB funds, ETFs, and individual stocks. The structure of the dataset is similar to that of the one used by Odean (1998): each observation specifies the account, date, time, price, quantity, and security code. The brokerage data include almost 3 million retail investors—around 5% of the entire investor population in China. Out of the 3 million investors, 1.2 million are considered "active"; that is, they both bought and sold at least 10 times during their transaction history. Table 4 presents summary statistics for the active investor population. We complement the transaction data with stock price, fund price, and NAV data from the China Stock Market and Accounting Research (CSMAR) database.

The second dataset contains survey responses to questions related to risk tolerance, self-reported wealth and income, self-reported financial literacy, investment horizon, investment experience, investment objective, and risk tolerance in the short run and in the long run. A detailed summary of these survey responses can be found in the Appendix. These surveys are voluntary when an investor opens her first account at the brokerage firm; on average, half of the investors take them. Because surveys are taken only once for each investor, certain information—such as investment horizon and objective—may be outdated. In spite of these limitations, we use survey responses in two contexts. First, in Sections 3 and 4, where we analyze the profit distribution across different investor groups, we use self-reported information on wealth and financial literacy. Second, in Section 5, where we analyze the entry decisions into B funds, we use these survey-based characteristics as control variables.

We construct a number of other variables using the data provided by this brokerage firm. First, we calculate investors' prior trading experience in other asset classes, such as warrants. Second, we construct a dummy variable for whether an investor holds a leverage account. Third, we use other investor demographic variables, such as age, gender, and education, which are provided to the brokerage firm when investors first open up their accounts. Finally, we observe the transactions for a small number of institutional investors that are linked to the brokerage firm and we discuss their behaviors in Section 4.

# 3 Wealth Implications of B Funds

## 3.1 Overview of B returns

In this section, we start with an overview of B fund returns from 2014 to 2015. Figure 3 plots the cumulative RMB returns and return rates for the entire sample of investors. They accumulated profits during the market run-up from December 2014 to May 2015. When the market peaked in early June, the entire sample was at a gain of a little over 2 billion RMB. Conditional on participation, this was almost 20,000 RMB per capita. These gains were almost completely wiped out during the market crash that started in mid-June. Due to their levered nature, B returns dropped sharply. By the end of 2015, B investors as a whole had approximately broken even.

While Figure 3 shows aggregate returns and overweighs wealthy investors with greater account balances, Table 5 presents the distribution of profits at the investor level. For comparison, returns are calculated for three sub-periods: during the quiet, during the run-up, and during the crash.[20] Panel A shows RMB returns. Consistent with Figure 3, while investors averaged profits of 11,070 RMB in the quiet period and 16,751 RMB in the run-up, these gains were offset by an average loss of 31,524 in the crash. We would expect the increase in the average profit from the quiet period to the run-up to be larger. However, many new investors entered during the later stages of the run-up and pushed down the average profit.

To further examine B returns across investors by controlling for the size of investment, Panels B to D present summary statistics for return rates based on three methods: first, returns are based

[20]The run-up period is December 1, 2014 to June 12, 2015; the crash period is June 15, 2015 to September 30, 2015; and the rest is the quiet period. See Liao et al. (2020) for a more detailed explanation about the timeline of the bubble.

on average maximum balance; second, on average balance; and third, on maximum investment.[21] Unsurprisingly, return rates are, on average, positive during the quiet period and run-up and negative during the crash. Return rates exhibit a large positive skewness in the run-up, but a large negative skewness in the crash. It is also worth noting that, across all three methods, the standard deviation of return rates is much higher during the crash than in the run-up and quiet periods. What explains this heterogeneity of returns throughout the bubble and especially during the crash? We address this question next.

## 3.2 Profit Distribution across Investors

Having shown that B investors broke even from 2014 to 2015, we now examine the distribution of returns across investor groups. In particular, we focus on two dimensions—wealth and sophistication—but we also pay attention to other characteristics, such as experience and gender.

### 3.2.1 Wealth

An increasing number of academic papers study rising wealth inequality in the US and the rest of the world (e.g., Cagetti and De Nardi 2006; Saez and Zucman 2016; Alvaredo et al. 2018). This discussion, in part due to Piketty's book (Piketty 2014), has grown beyond the confines of academia and is an important consideration for leading politicians (Sanders 2020). One of the most striking findings about rising wealth inequality is that wealthier individuals appear to be systematically earning higher returns on their financial investments. This can be traced back to their differences in market timing skills, private information about individual stocks, and portfolio diversification (An et al. 2019; Campbell et al. 2019; Fagereng et al. 2020). Our results suggest that financial innovation may also contribute to this wealth gap.

While wealth is notoriously difficult to measure without administrative records (Fagereng et al. 2020), we use two plausible proxies. The first is account size, measured by the maximum account balance prior to 2014 to avoid any look-ahead bias (An et al. 2019; Campbell et al. 2019). For size,

[21] Calculating return rate at the investor level is notoriously difficult due to different ways to construct the average invested capital. In this paper, we adopt three ways to measure an investor's investment in B funds in each sub-period. The first is the maximum balance, which effectively measures the maximum investment that existed in the account at the end of the day. The second is the average balance to date, where average balance is calculated daily. The third is maximum investment, which measures the initial account balance at the beginning of each sub-period plus the maximum cumulative net flows into B funds during that sub-period.

we compare those in the top 1% and those in the bottom 99%, with 5 million RMB as the cutoff point.[22] The second proxy is self-reported wealth, taken from survey data. There are two caveats with this proxy: only half of the investors report their wealth and their answers are not as granular as size. We therefore use 1 million RMB as the cutoff value for wealthy groups.

Figure 4 plots cumulative RMB returns and return rates for investor groups sorted by wealth. The most salient observation is that the total profit was asymmetrically distributed: wealthier investors made a large profit and poorer investors took a substantial loss. Sub-figure 4a shows that the top 1% made a total profit of 500 million RMB, whereas the bottom 99% lost 500 million RMB, resulting in a wealth transfer—or a difference in total profits—of 1 billion RMB from the poor to the rich. Similarly, Sub-figure 4b shows that those with wealth above 1 million RMB made a total profit of 500 million RMB while those with wealth below 1 million RMB lost 200 million RMB, suggesting a wealth transfer of 700 million RMB. Because our data cover around 5% of the entire investor population, these numbers suggest a total wealth transfer of 14 to 20 billion RMB from the poor to the rich in just two years.

Sub-figure 4a shows that most of the difference in returns occurred during the market crash. The return difference between large and small investors grew steadily during the run-up but remained relatively small. However, the gap widened substantially during the crash: in just two months, it rose to over 1 billion RMB. We see a similar pattern in Sub-figure 4c for return rates.[23]

### 3.2.2 Sophistication

We next examine sophistication. As with wealth, we use two measures. The first is based on self-reported financial literacy, taken from the survey data; we classify investors as high-literacy or low-literacy (Van Rooij et al. 2011; Lusardi and Mitchell 2014). The second measure is based on their highest education level; we sort investors into two groups based on whether they have earned a college degree or not. Figure 5 plots returns for investor groups sorted on their levels of financial literacy and education. As in Figure 4, sophisticated investors harvested most of the profit while the naive investors suffered. The magnitude of the gap, however, is a bit smaller: there is a wealth transfer of 400 million from the low-literacy group to the high-literacy group and 500 million from

[22] Results are robust to changes of this cutoff value (e.g., 5% or 10%).

[23] Due to differences in initial investment, this pattern is less observable in Sub-figure 4b. Sub-figure 4d shows a similar pattern in terms of return rates.

the non-college-educated group to the college-educated group. Extrapolating these numbers to the entire population suggests a total wealth transfer of 8 to 10 billion RMB from the naive to the sophisticated.

We find a similar pattern for return rates and, again, most of the difference in return rates came during the crash, as shown in Sub-figures 5c and 5d. In Section 4, we directly confront this pattern. We argue that one of the main reasons that rich and sophisticated investors did better during the crash is that they knew how to deal with the downside risk shrouded by complexity.

#### 3.2.3 Experience and gender

Finally, we examine two other investor characteristics. The first is experience. Prior literature shows that experience matters for the perception of risk (Malmendier and Nagel 2011), the formation of expectations (Malmendier and Nagel 2016), fund managers' behaviors during a financial bubble (Greenwood and Nagel 2009), and corporate decisions (Malmendier et al. 2011). In our paper, we sort investors into two groups: "experienced"—those who were trading B funds before the run-up to the bubble—and "novice"—those who started trading B funds only during the run-up. We compare their returns right before the peak and during the crash. The returns before the peak may be subject to a selection bias: those who entered during the run-up may be in the middle of building their positions and could have missed part of the run-up. However, for returns during the crash, there should be less selection bias since both groups had already been trading for at least a month before the crash. In Sub-figure 6a, we see a 1.5-billion-RMB difference in returns between the novice group and the experienced group. Extrapolating this wealth transfer to the entire investor population suggests a total wealth transfer of 30 billion RMB from the inexperienced to the experienced. Sub-figure 6c shows a similar pattern for return rates.

As for gender, prior literature suggests that men are more overconfident than women and excessive trading makes men underperform in stock markets (Barber and Odean 2001). More recently, Goldsmith-Pinkham and Shue (2019) show that women perform substantially worse in real estate markets. What about trading complex financial products? In Sub-figures 6b and 6d, women performed better trading B funds than men, particularly during the crash. We leave a deeper exploration of this pattern to future research.[24]

[24] One caveat to note about this gender effect is that the sign flips for returns during the crash in cross-sectional

#### 3.2.4 Regressions

To establish the observations from Figures 4 to 6 in a cross-sectional regression framework, we regress investor-level return rates on various investor characteristics in a series of univariate regressions. Throughout the paper, we use the most conservative return rate based on maximum balance; in the Appendix, we show that the results are robust to alternative measures of return rates. Consistent with the patterns illustrated by the figures, Table 6 shows that most of the difference in return rates was driven by the crash. For instance, while the dummy for wealth over 1 million RMB has a positive coefficient of 0.5% in the run-up, the coefficient's magnitude more than quadruples during the crash. Similarly, the dummy for financial literacy increases from 0.9% in the run-up to 2.5% in the crash. Overall, the demographic variables we consider much better explain crash returns than run-up returns.

## 3.3 Comparison with ETFs

In the previous section, we showed that B funds induced a substantial wealth transfer from the poor to the rich, from the naive to the sophisticated, and from the inexperienced to the experienced. However, given the mounting evidence that returns increase with the level of wealth, the direction of these wealth transfers may not be shocking.

Our goal is not simply to document the existence of such wealth transfers; indeed, An et al. (2019) has already shown that the bubble-and-crash episode induced a large wealth transfer from small to large investors. Instead, we want to examine what fraction of these wealth transfers is due to the *complexity* of B funds. Towards this end, a natural counterfactual—one without these complex features of time-varying leverage and hidden restructuring clauses—is to examine wealth transfers from trading (simple) ETFs. Indeed, just as MBSs are derived from a pool of mortgages, structured funds are the product of financial engineering based on traditional mutual funds. A second desirable feature of ETFs, as shown in Figure 1b, is that, around the peak of the bubble, their total market size was about the same as that of structured funds. This means that the average portfolio weights of ETFs and B funds were comparable. As a benchmark, Figure 7 plots the cumulative returns from trading ETFs for the *same* group of investors. Overall, they did much

regressions. Therefore, the gender effect we have documented here may not be very robust.

better trading ETFs, making a total profit of around 300 million RMB.

Figure 8 plots total RMB profits for different investor groups. To make an appropriate comparison with the previous results, all figures are plotted using the same scales as in Figure 4. Looking at the graphs is sufficiently telling: in most figures, the scale of wealth transfer, if any, is less visible. In Sub-figure 8a, small investors actually make more profits than large investors due to a greater initial investment. In Sub-figures 8b and 8c, the direction of the transfer is consistent with that for B funds, but the magnitude is much smaller. Figure 9 further plots the return rates for different investor groups by controlling for their differences in total investment. In most cases, return rates are very similar across investor groups through both the run-up and the crash, which is in sharp contrast to the patterns documented in Figures 4 to 6.

Table 7 puts all the six variables we have considered so far in the same regression. In Columns 2 and 3, size, financial literacy, and experience are all positive determinants of B fund returns during the crash, whereas, in Column 6, they are not positive determinants of ETF returns. Specifically, we find that, compared to the average investor, those identified as being in the top 1% of wealth earned about 3.6% higher returns trading B funds, but not higher returns trading ETFs, during the crash. Similarly, those with higher financial literacy earned about 2.3% higher returns trading B funds than low-literacy investors in the crash, but their difference in returns from trading ETFs was essentially zero. Finally, as shown in Column 4, these results are robust to the inclusion of ETF return as a control variable. This suggests that the factors that can be used to explain differences in ETF returns, such as market timing, cannot account for the observed heterogeneity in B returns.

The difference in wealth transfer sizes between ETFs and B funds cannot be explained solely by the scaling effect of leverage. First, as Figure 8 shows, small and naive investors earned *positive* profits or broke even trading ETFs. A scaling effect would make their profits even greater and cannot generate the negative profits we observe for B funds in Figure 4a. Second, as shown in Figure 9, ETF return rates were quite similar across investor groups so that scaling them up would not make their differences much bigger.

However, it is possible that leverage exacerbates behavioral biases and makes naive investors more prone to bad investment decisions (Heimer and Simsek 2019; Heimer and Imas 2020). In this case, the effect of leverage goes beyond a scaling effect and a more appropriate comparison should be carried out between structured funds and levered ETFs with a constant leverage ratio.

Unfortunately, such products are not available in the Chinese markets. Instead, in Section 4, we rely on restructuring events to identify the effects of complexity.

Because both B funds and ETFs are designed to trace some underlying equity indexes, the two asset classes are very similar in the types of stocks they cover. However, there are a few exceptions where the equity index traced by a B fund is not covered by an ETF, or vice versa. To correct for these small differences, we repeat the exercises in Sections 3.2 and 3.3 by narrowing our sample down to B funds and ETFs that share a common index; the results are reported in the Appendix. All the above patterns are robust in this slightly smaller set of funds.

# 4 Restructuring Events

The comparison between B funds and ETFs in Section 3 showed how adding complexity to simple securities can lead to a much greater wealth transfer. In this section, we provide direct evidence of how complexity induces this wealth transfer. In particular, we zoom into the 2015 market crash, which triggered 52 funds into a restructuring process. As we demonstrate below, these restructuring events, jointly driven by the product's two complex features, carry direct and substantial implications for investor wealth. Therefore, they provide an ideal setting for studying how investors respond differently to complexity. We thus also address a robust pattern documented above: most of the wealth transfer occurred during the crash.

## 4.1 Overview of restructuring events

Once the per-share NAV of a B fund drops below a threshold value, typically set at 0.25 RMB, a restructuring process is underway. Once triggered, it usually takes two days. Day 0, known as the "event day," is when B's per-share NAV falls below 0.25 RMB. On day 1, trading continues. However, even if per-share NAV goes back above 0.25 RMB at the end of that day, restructuring cannot be reversed. On day 2, known as the "restructuring day," trading suspends and leverage is reset according to the NAV at close on day 1. Trading resumes on day 3.

To give a concrete example, consider Penghua One-Belt-One-Road B Fund. Sub-figure 10a shows that, from June 24 to July 7, 2015, its per-share NAV dropped from 0.81 to 0.29. At the same time, the premium rose from 23% to almost 74%. On July 8, the NAV closed at 0.24, which crossed the 0.25 threshold for the first time and triggered the restructuring event. Restructuring was scheduled to take place on July 10 (Friday) and trading continued on July 9. Indeed, as Sub-figure 10b shows, there was intensive trading on July 9. After restructuring, trading resumed on July 13 (Monday) with the leverage ratio reset to 1:1. The premium, however, disappeared on July 13, and an investor who held Penghua B shares on July 9 would suddenly find their value halved.

The Penghua experience was not unique. In Figure 11, Sub-figure 11a plots the evolution of price and NAV, averaged across the 52 restructuring events, during the 21-day window around the event day. During the 11-day window before the event day, per-share NAV experienced a steady decline from 0.63 to 0.22, a 65% drop. This was associated with a sharp increase in embedded leverage from 1.59 to 4.55 and an increase in premium from 18.3% to 101.1%. When trading resumed on day 3, however, this 101.1% premium was almost completely wiped out.

While it is clear *ex-post* that leverage resets eliminated the B premium, could investors figure this out *ex-ante*? We believe so for three reasons. First, as we discussed in Section 2.2.2, most of the variation in B premium was driven by leverage. Therefore, knowing that the high leverage would reset to 1, an investor should rationally expect the associated premium to drop. Second, while most of the premium was driven by leverage, part of the premium, especially on days $-1$ and 0, was induced by the daily price limit rule imposed by the regulator—the China Securities Regulatory Commission (Chen et al. 2019).[25] After the leverage reset, however, trading would resume at the price of the new NAV, which would directly eliminate the part of the premium induced by the rule. Third, restructuring events came in waves and the time gaps in between gave room for learning. For instance, the first wave was in early July, when 18 funds went into restructuring, and the next wave came almost two months later in late August. This two-month window should allow attentive investors to learn about the nature of these events.

After seeing consecutive drops in the NAV, a fully informed, rational investor should have a clear path of action. First, as the NAV approaches the restructuring threshold, the probability of restructuring increases dramatically. Knowing that restructuring means the disappearance of the premium, a rational investor should start selling her existing positions in B funds to avoid downside risk. Second, even if, for some reason, she was left with a positive position in B by the event day,

[25]The rule says that, within a single trading day, the price of an individual security can only increase or decrease by a maximum of 10% relative to the closing price on the previous trading day. We discuss the implications of this trading rule for the B premium in the Appendix.

she still had a chance to get out: because trading continues on day 1, she should try to sell as much as possible on that day.

How did investors actually respond? Sub-figure 11b plots the cumulative trading flow during the 21-day window around the event day. It turns out that retail investors as a group engaged in the exact opposite trade. During the 11-day window before the event day, they increased their holdings by more than 13%. More strikingly, they further increased their holdings by another 3% on day 1, even though restructuring was set to happen the next day. After the restructuring events, trading remained fairly stable and experienced a slight outflow towards the end of the 21-day window. During the 11-day window before the event day, B traders registered a total loss of over 500 million RMB. Moreover, they lost over 400 million additional RMB on day 2 as leverage was reset. In total, they lost around a billion RMB in this 13-day window. The loss on the restructuring day was particularly striking: it alone accounted for more than 15% of their loss in the crash.

A possible explanation for the lack of response is that investors wanted to trade but there was no liquidity during the market crash. However, the lack of liquidity cannot justify the *buying* on day 1. Moreover, Figure 11c plots the daily trading volume during the 21-day window. Overall, there was plenty of liquidity prior to restructuring, with tens of millions of shares traded daily. In fact, the average trading volume on day 1 was more than 150 million shares, suggesting that investors were able to get out even at the last minute.

The losses we have documented in Sub-figure 11b are conditional on the eventual realization of a restructuring event. It is possible that some funds that were on the edge of restructuring might have rebounded and that the losses were offset by the positive returns from funds that resurrected. However, notice that a drop in NAV also means a jump in the embedded leverage, which makes B's NAV even more sensitive to changes in the parent's NAV. Thus, even a small drop can make B cross the restructuring threshold. We find, in fact, that few funds resurrected, which suggests that even investors with gambling preferences should liquidate near the restructuring threshold. To show this, Sub-figure 11d plots the post-event retail flows and returns, where the event is defined by the first time a fund drops below 0.35.[26] Consistent with the above discussion, the post-event returns were largely negative.

[26]Results are robust to alternative cutoff values such as 0.3 or 0.4.

## 4.2 Heterogeneous flow responses and returns

The previous section showed that investors on average were unaware of the negative consequences of restructuring events and suffered substantial losses by trading in the wrong direction. But did some investor types handle restructuring events better?

Figure 12 shows the cumulative trading flows during the 21-day window around the event day for investor groups sorted on wealth and sophistication. In Sub-figure 12a, B funds had a net outflow of around 10% from the top 1% of investors in the 11-day window prior to the event day. This suggests that they gradually took money out in anticipation of the restructuring events. During the same period, the bottom 99% of investors had a net inflow of almost 20%, suggesting they were unaware of the hidden downside associated with restructuring. As a result, the difference in cumulative returns between the two groups rose to almost 12% on the event day. Furthermore, due to their net inflow into B funds, the restructuring events hit the bottom 99% particularly hard and the difference in returns rose to 18% after the restructuring events. The differences in returns and trading flows remained rather stable after the restructuring events.

A similar pattern can be found in Sub-figures 12b to 12d, albeit with a slightly smaller magnitude. For instance, in Sub-figure 12c, high-literacy investors had a much smaller net inflow into B funds than the low-literacy group. As a result, the gap between their cumulative return rates reached 10% after the restructuring events. Overall, the results suggest that the wealthy and sophisticated investors handled restructuring events better than poor and naive investors.

How much of the wealth transfers documented in Figure 4 can be attributed to these restructuring events? Figure 13 addresses this question by presenting wealth redistribution across wealth buckets. Across the 21-day window, the top 1% investors lost about 150 million RMB while the bottom 99% lost a little less than 600 million RMB. The difference in returns began to accumulate as NAV approached the threshold. However, it was the restructuring day that drove most of the difference: the bottom 99% lost another 250 million RMB that day. Therefore, for the 1 billion RMB transfer shown in Figure 4a, we can attribute 25% to the restructuring day and 45% to the 21-day window.

## 4.3 Mechanisms

The results so far highlight two properties of the effects of retail structured funds on wealth redistribution. Section 3 shows that structured funds induce a greater wealth transfer from the poor (and naive) to the rich (and sophisticated) than nonstructured funds. Sections 4.1 and 4.2 show that a significant fraction of such wealth transfer *can* be directly explained by poor and naive investors' confusion and/or ignorance. In this section, we discuss alternative explanations for these results.

### 4.3.1 Liquidity provision

One possible explanation for the better performance of large investors is that they make money by acting as market makers and providing liquidity. For instance, in a related study, Li et al. (2020) find that large investors act as liquidity providers in the Chinese warrants market. *Ex-ante*, we find this explanation unlikely to account for our results. Many of the top 1% investors outperformed because they were able to exit the market before the market crashed or restructuring took place. It is unlikely that market makers would completely exit the market.

To formally test this explanation, we follow Li et al. (2020) and identify the likely liquidity providers in the market. Specifically, among the top 1% of investors, we first consider those with a positive account balance for at least 120 days (corresponding to the 75th percentile in the distribution). Within this subset, we identify liquidity providers as those with a turnover above the median. Sub-figures 14a and 14b plot the returns of liquidity providers and non-liquidity providers, respectively, and shows that liquidity providers do not make more profits than non-liquidity providers. In fact, during the crash, liquidity providers injected liquidity to the market by increasing their holdings but lost money as the market continued to drop.

### 4.3.2 Liquidity shock

A second explanation for the better performance of large investors is that, during the market crash, they had to take money out of the stock market due to a negative shock elsewhere, which, by sheer coincidence, helped them escape the disastrous consequences of restructuring. To entertain this possibility, we study investors' cash holdings at the brokerage accounts to examine their liquidity needs. Figure 15 plots these patterns from 2014 to 2015. Figure 15a shows that, while the average cash holdings evolve in parallel during the market boom, the top 1% investors begin to hold more cash during the crash. This is also reflected in Figure 15b: a greater fraction of their account balance is held in cash during the crash. Therefore, large investors appeared to have better liquidity than smaller investors.

#### 4.3.3 Reluctance to realize losses

A third explanation for the better performance of large investors, especially during the crash, involves the mechanisms of the disposition effect (Odean 1998); that is, the propensity to realize gains and avoid losses. Rich and sophisticated investors display a weaker disposition effect (Dhar and Zhu 2006). Therefore, they may be more likely to sell during the crash and avoid greater losses as prices go down even further because they are not reluctant to realize their losses.

We proxy for a reluctance to realize losses with a measure of the disposition effect based on transactions of individual stocks. Sub-figures 14c and 14d plot the returns for high- and low-disposition-effect investors. The two groups exhibited similar returns from 2014 to 2015. Sub-figure 14e further plots their trading flows during restructuring events and shows parallel patterns. This suggests that the reluctance to realize losses cannot explain people's behavior during restructuring events.

#### 4.3.4 Inattention

A fourth explanation, particularly relevant to trading behavior during restructuring events, is investor inattention (see Gabaix (2019) for a recent review). It is possible that poor and naive investors, while fully aware of the product's complex features, were less attentive to the stock market and therefore did not trade in the right direction. One possible driver of inattention is the so-called "ostrich effect": after bad returns hit, investors choose to ignore the stock market and not look at their trading accounts anymore (Sicherman et al. 2016; Olafsson and Pagel 2017). While this in principle could explain why many investors did not decrease their positions, it does not explain why on average they *increased* their positions before the restructuring events took place, a pattern shown in Sub-figure 11b.

To further examine this explanation, we sort investors into groups based on their turnover of individual stocks, a proxy for attention to the stock market, in June, 2015—the month right before restructuring started to take place. Sub-figure 14f plots their trading flows around the restructuring events. While, indeed, investors with a low turnover rate remained quite inactive, those with a higher turnover *increased* their holdings substantially. Therefore, investor inattention is unlikely to be the explanation for investors' differing responses during restructuring events.

#### 4.3.5 Why did small investors increase their positions?

Our discussion above suggests that competing explanations based on liquidity provision, liquidity shocks, behavioral biases such as the disposition effect, and inattention cannot account for the observed differences of responses between the rich and sophisticated investors and the poor and naive investors. We therefore conclude that the most likely explanation is that the former group understand these products better and are able to navigate when a downside event occurs.

However, if a naive investor does not understand the nature of restructuring events and the complex features of structured funds, it remains a mystery why she would *increase* her holdings rather than do nothing. In this section, we focus on the behavior of the bottom 99% and try to understand why they increased their holdings. We propose two main explanations that are not mutually exclusive and can partially explain this increase: gambling preferences and borrowing constraints. In fact, these explanations may be complementary: gambling preference leads to more leverage seeking when investors are constrained in their ability to borrow.

We measure an investor's gambling preference by whether she has traded warrants before. Because warrants have nonlinear payoffs, having traded them before suggests a tendency to gamble by revealed preferences.[27] Sub-figure 16a shows that, consistent with gambling preference, investors who have traded warrants increased their holdings more prior to restructuring.

We examine the role of borrowing constraints with two proxies. The first is the amount of cash as a fraction of total balance in the account. The assumption here is that those who have less cash in their accounts are more constrained. The second proxy is whether or not one has a margin account, where having a margin account allows an investor to borrow money from her broker and therefore proxies for less constraint. In Sub-figures 16b and 16c, we find that investors under both sets of constraints increased their holdings more than unconstrained investors prior to restructuring.

[27] We acknowledge that this proxy is not perfect, as having traded warrants before may also be correlated with other factors such as investor sophistication.

## 4.4 Other discussions

### 4.4.1 The behavior of issuers

An important feature of our setting is that, after issuance, brokers are largely absent from the secondary market and are not able to use their private information to screen out certain investors. However, they still play a role in the initial design of the contract and it would be informative to know about the extent to which they inform investors about restructuring risk in their prospectuses. We collect the initial prospectuses and examine their contents.[28] On average, a prospectus is about 130 pages long, but the discussion of risk is only 5 pages and does not start until page 86. Virtually all prospectuses discuss the premium associated with the leverage and the existence of restructuring events, suggesting that issuers were aware of the potential losses in the restructuring events. However, only three prospectuses explicitly discuss the risk associated with restructuring. Therefore, consistent with Bordalo et al. (2012) and Célérier and Vallée (2017), issuers in our sample appear to shroud this restructuring risk in a lengthy and wordy prospectus.[29]

### 4.4.2 The behavior of institutional investors

Due to data limitations, we only observe dozens of institutional investors, giving us only limited power to generalize their behavior during this episode.[30] However, even this small set may yield insights about the behavior of institutions. Sub-figure 17a plots their trading behavior during restructuring events and shows that institutional investors as a whole decreased their holdings by almost 70% prior to the restructuring events. Sub-figure 17b further narrows down to the more "active" participants, who almost completely liquidated their positions prior to the restructuring events. Therefore, institutional investors were largely on the other side of the trade by selling their shares to retail investors, dumping all the risks to the most vulnerable group.

[28]A more detailed analysis of these prospectuses is included in the Appendix.

[29]A potentially informative exercise is to examine whether investors deal with complexity better when issuers explicitly discuss the restructuring risk. Unfortunately, power is limited in our setting, since only three funds made an explicit disclosure of this risk.

[30]We require an institutional investor to have at least 100 fund-day observations from 2014 to 2015 to be included in our analysis.

### 4.4.3 Behavior of A funds during the restructuring events

Most of our analysis so far has been devoted to B funds, because their leverage feature made them immensely popular during the 2015 Chinese stock market bubble. However, the behavior of A funds is equally interesting: as "safe" assets, they were at one point trading at a 20% discount. Although further analysis of A funds is beyond the scope of this paper, we note that many large sophisticated investors who pulled out from B funds prior to the structuring events re-invested the proceeds into A funds, thereby making further profits from the resets. If we take into account the profits large investors made from trading A funds, the overall wealth transfer will be substantially greater.

# 5 Entry Decisions

In the previous sections, we showed that many investors, especially the poor and naive subset, suffered substantial financial losses by investing in B funds. If the ex-post returns are so bad, why do investors buy into B funds in the first place? This is especially puzzling in light of the experimental evidence that people are averse to complexity (Carlin et al. 2013). In this section, we show that the entry decisions into B funds were primarily driven by their salient "upside" feature: cheap leverage. In particular, during the market boom, levered B funds delivered higher returns than the market did, and return-seeking investors were lured by these high returns without understanding their features in full.

To be more specific, for the run-up period, which witnessed most of the new entries into B funds, we estimate regressions of the following form for an individual $i$ who has *not* purchased B funds as of month $m-1$:

$$\text{Dummy}^{B}_{i,m}100 = \alpha + \Theta \times \text{Determinants}_{i,m-1} + \varepsilon_{i,m}, \tag{1}$$

where $\text{Dummy}^{B}_{i,m}$ equals 1 if $i$ trades B in month $m$ and 0 otherwise and $\text{Determinants}_{i,m-1}$ represent various account characteristics based on transactions made up to month $m-1$. In other words, in each month, we examine what factors trigger the decision to start investing in B funds among those who haven't traded them yet.

We consider an exhaustive list of possible determinants for trading B funds, including: extrapolation (Barberis et al. 2015; Bordalo et al. 2016; Barberis et al. 2018; Liao et al. 2020), demand for leverage (Bian et al. 2018a,b), trading experience (Seru et al. 2010), account size (An et al. 2019; Campbell et al. 2019), disposition effect (Odean 1998), gambling preference (Kumar 2009), and other standard trading characteristics such as performance, turnover, and degree of diversification. To avoid capturing mechanical relationships between these variables and the entry into B funds, these variables are all constructed using retail investors' individual stock transaction data. We also include survey responses as control variables. Details about the construction of these variables and the survey can be found in the Appendix.

Column (1) of Table 8 reports the results for regressing past market returns on future entry and shows a significant positive relationship between the two. Indeed, most entries take place after the market experiences a sharp rise in the previous month: a 10-percentage-point increase in market return is associated with a 0.9-percentage-point increase in the probability of entry in the next month. Given that the average adoption rate is around 10%, the magnitude is rather large. In Column (2), we interact past stock market returns with measures of extrapolation. Interestingly, while extrapolation itself is not significant, its interaction term with market returns is highly significant with a large and positive coefficient. This suggests that extrapolators are much more likely to start trading B funds than non-extrapolators after the market has been rising for a while. Given that market returns are highly correlated with B returns, extrapolators take the positive market returns as a sign to enter the market.

In Column (3), we include a long list of controls. While all results in the first three columns remain robust, some additional variables also appear significant and are worth nothing. First, inexperienced investors are more likely to trade B funds. Second, large investors are more likely to trade B funds. Third, consistent with gambling preference, investors who have traded warrants before are more likely to trade B funds. Fourth, investors who trade more often are more likely to trade B funds. Column (4) includes additional controls based on survey responses and shows essentially the same pattern.

# 6 Conclusion

Complex financial products can be welfare improving. With perfectly rational investors, complex products can better distribute risk than their simpler counterparts. However, there is a growing literature that documents their dangers, showing that issuers can use complexity to enrich their coffers by tricking unsophisticated investors into buying products at inflated prices. We add to this literature by showing that the dangers of complex products to the unsophisticated extend beyond issuance. Specifically, we show that, even in a setting devoid of marketing considerations (such as exchange-based trades), the unsophisticated suffer in terms of trading performance at the hands of the sophisticated. This has new implications for the regulation of complex financial products and motivates future work on how to best protect naive investors from complex products in settings in which brokers play little role.

There is also growing evidence that investment returns on wealth increase with wealth. We provide evidence that increasing the complexity of financial products may shed light on this empirical fact. Specifically, we show that the wealthy successfully traded complex financial products in China at the expense of the poor. We offer evidence that a significant part of this wealth transfer can be attributed to the products' complexity and point to complexity as a potential driver of differing investment returns across wealth levels. Given the large and growing importance of structured financial products in the global economy, this could be an important factor in the distribution of returns on wealth.

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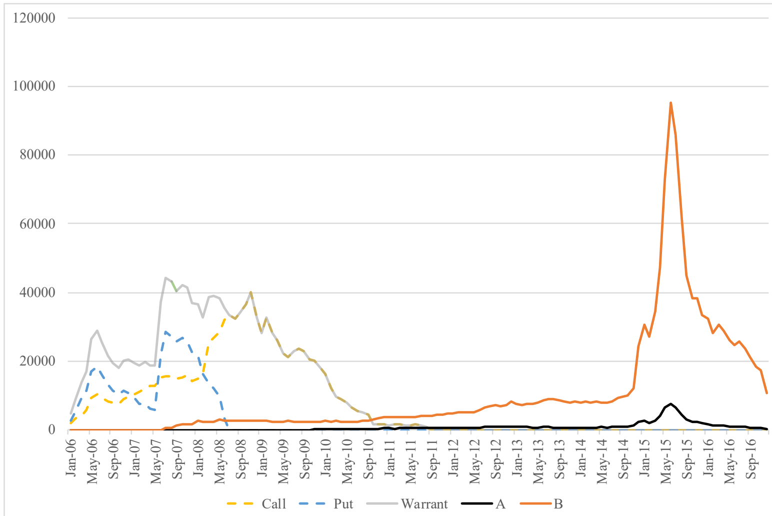
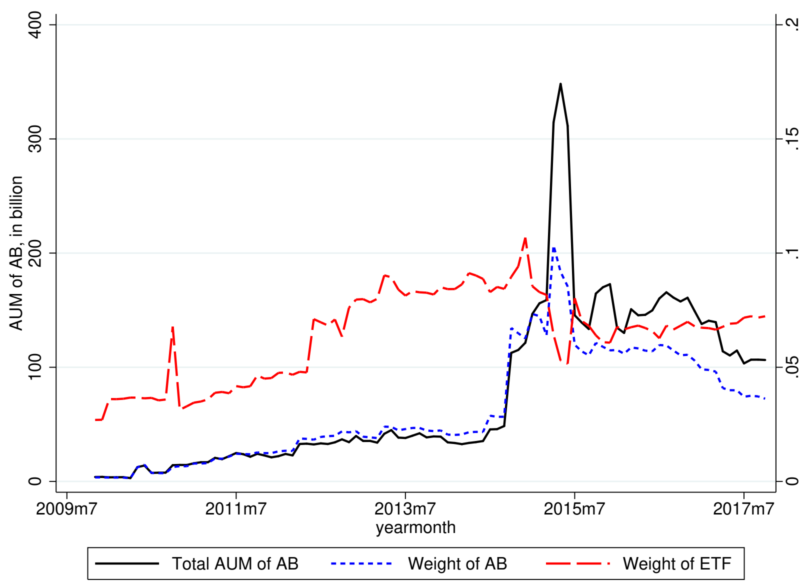



(a) Popularity




(b) Market size of structured funds

Figure 1: Popularity and Market Size of Structured Funds

Note: Sub-figure 1a plots the number of accounts holding a particular type of asset in their month-end portfolios from 2006:01 to 2016:12. The five lines correspond to: call warrants, put warrants, all warrants, A funds, and B funds. Sub-figure 1b plots the total market size for AB funds and other ETFs from 2009 to 2017. The solid black line represents the total assets under management for AB funds, with scale plotted on the left axis. The blue dashed line represents the fraction of total mutual fund AUM accounted for by AB funds. The red dashed line represents the fraction of total mutual fund AUM accounted for by other ETFs, with scale plotted on the right axis.

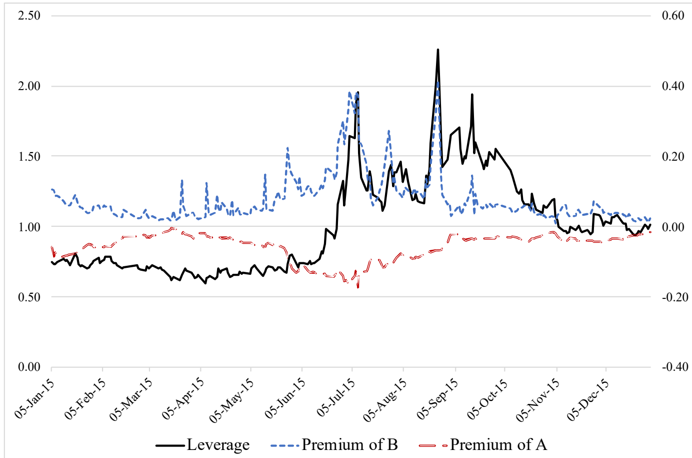



Figure 2: Time-series Variations of Leverage and Premium

Note: Dynamics of the leverage and premium of AB funds during 2015. Leverage is calculated by dividing the per-share NAV of an A fund by the per-share NAV of the corresponding B fund. Premium is calculated by dividing the difference between price and NAV by NAV. We then take the simple averages of these measures across all funds.

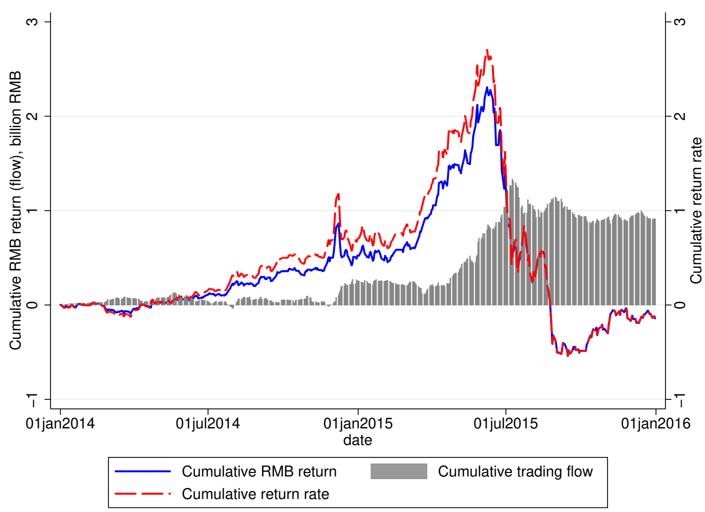
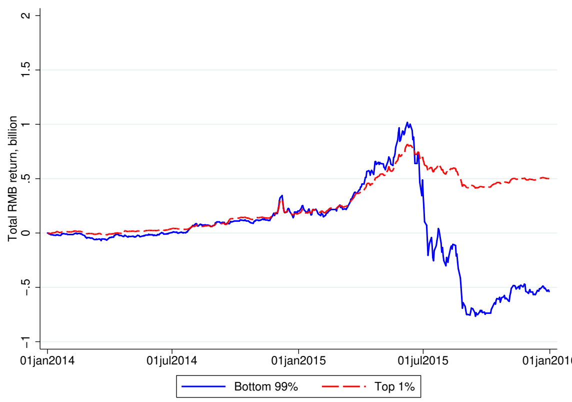
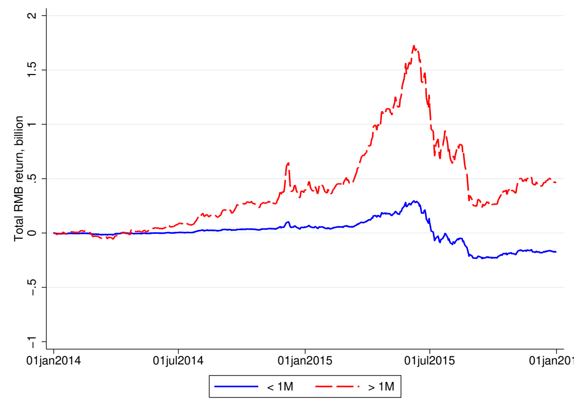



Figure 3: Cumulative Returns and Trading Flows of B Funds, 2014-2015

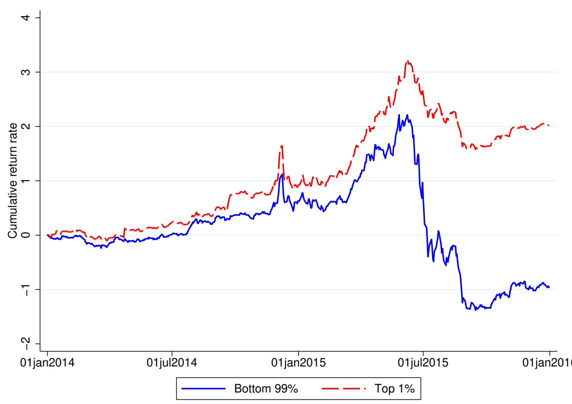
Note: Cumulative returns and flows from B funds from 2014 to 2015. The blue solid line represents the cumulative RMB return from trading B funds. The grey bar represents the cumulative trading flow into B funds. Both series are scaled using the left axis. The red dashed line represents cumulative return rate, calculated by cumulative RMB return by average investment calculated based on daily investment.



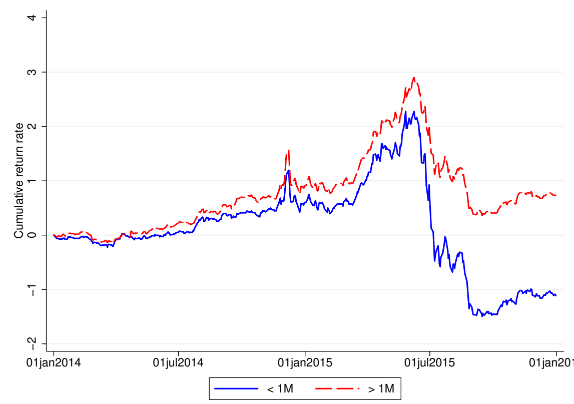

(a) RMB return for size groups




(b) RMB return for wealth groups



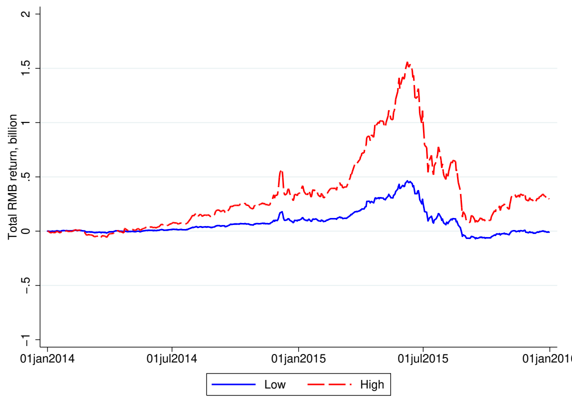

(c) Return rates for size groups



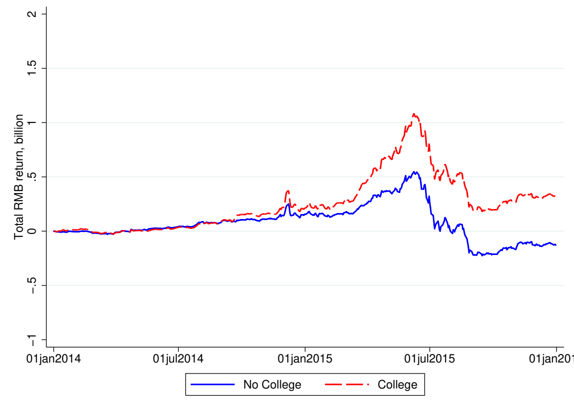

(d) Return rates for wealth groups

Figure 4: B Fund Returns for Investor Groups Sorted by Wealth

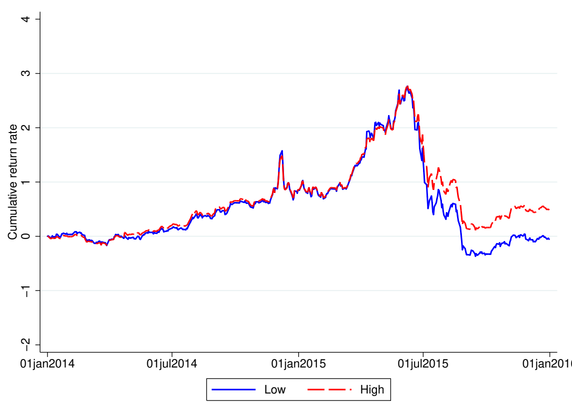
Note: Cumulative returns from B funds from 2014 to 2015 for investors of different wealth levels. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth level. Return rates are calculated by dividing total RMB return by average daily balance.



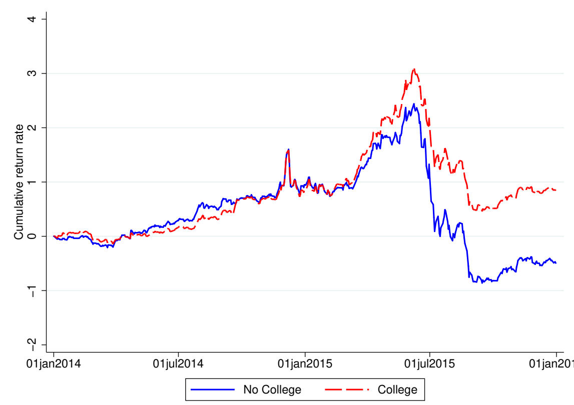

(a) RMB return for literacy groups




(b) RMB return for education groups



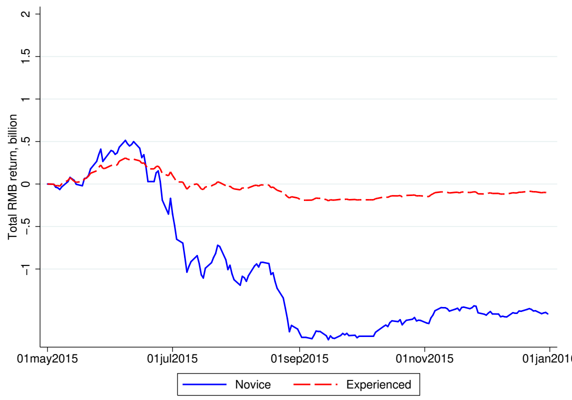

(c) Return rates for literacy groups



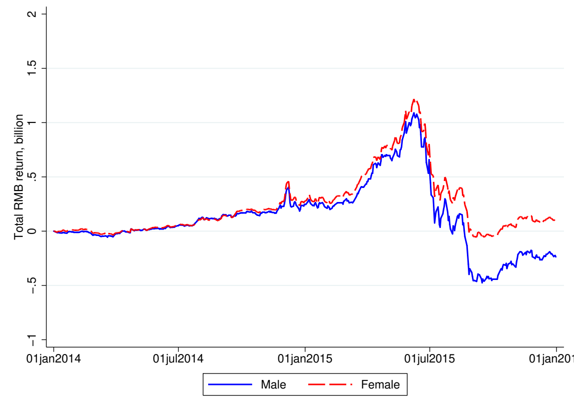

(d) Return rates for education groups

Figure 5: B Fund Returns for Investor Groups Sorted by Financial Literacy and Education

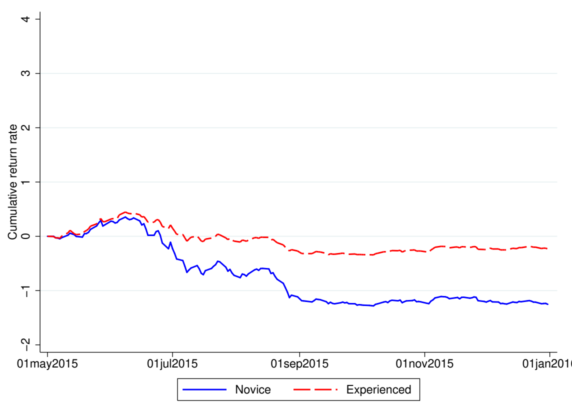
Note: Cumulative returns from B funds from 2014 to 2015 for investors of different levels of education and sophistication. High financial literacy indicates self-reporting good financial knowledge and practical skills. Return rates are calculated by dividing total RMB return by average daily balance.



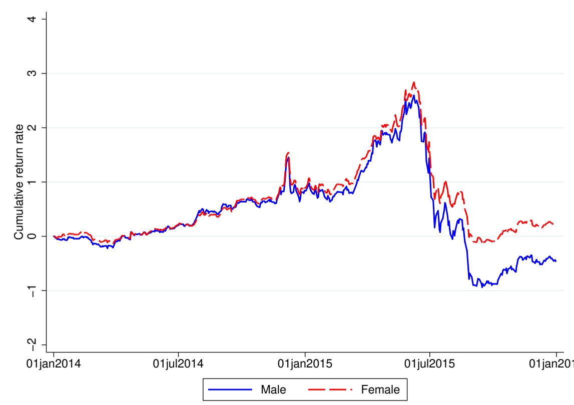

(a) RMB return for experience groups




(b) RMB return for gender groups




(c) Return rates for experience groups




(d) Return rates for gender groups

Figure 6: B Fund Returns for Investor Groups Sorted by Experience and Gender

Note: Cumulative returns from B funds from 2014 to 2015 for investors of different experience and gender. The Experienced with B group is constructed by including those who started trading B funds before the run-up of the bubble. Return rates are calculated by dividing total RMB return by average daily balance.

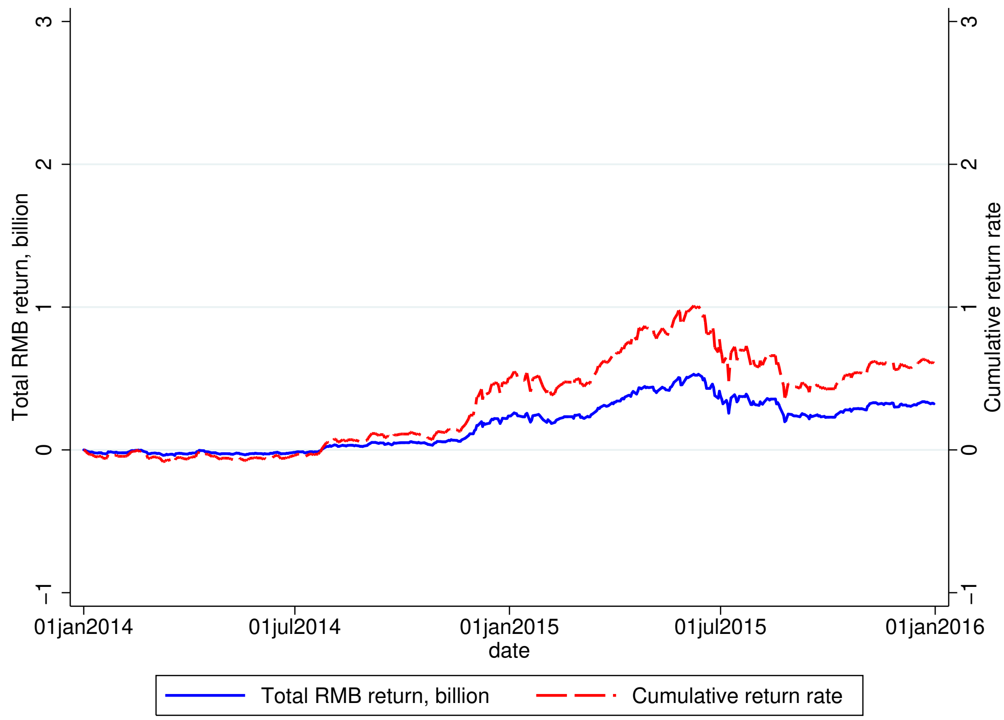
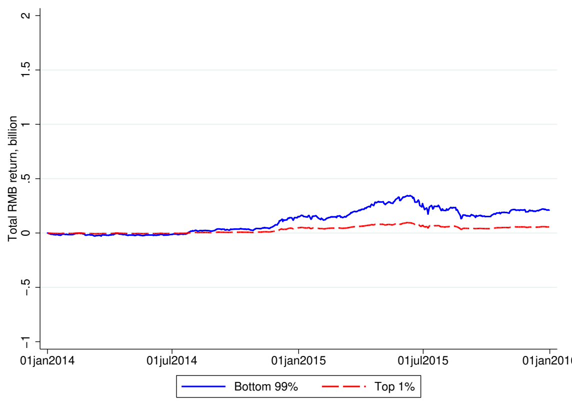
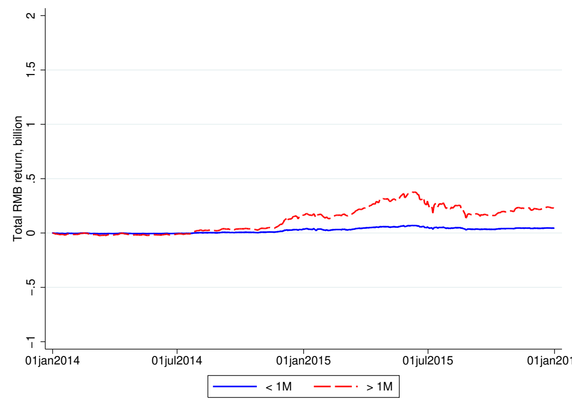



Figure 7: Cumulative Returns from ETFs, 2014-2015

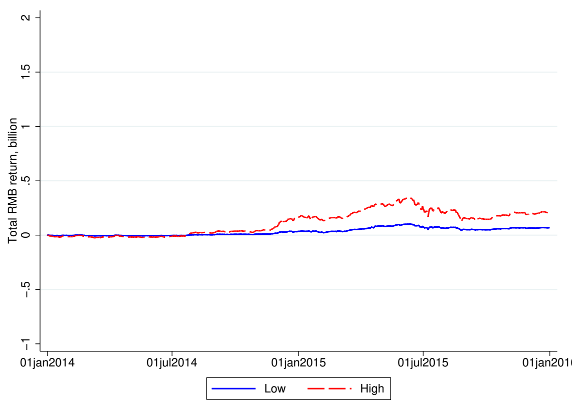
Note: This figure plots cumulative returns and flows from ETFs from 2014 to 2015. The blue solid line represents the cumulative RMB return from trading B funds. The red dashed line represents cumulative return rate, calculated by cumulative RMB return by average investment.



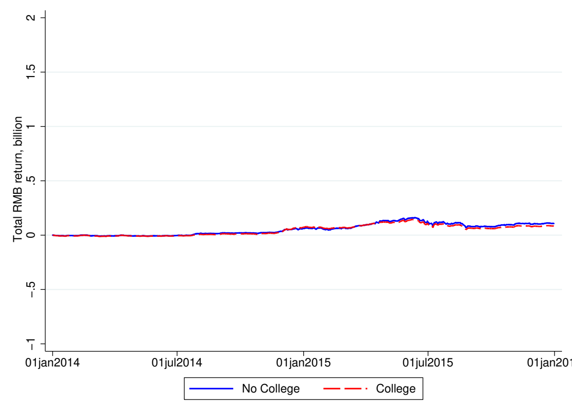

(a) Size




(b) Wealth



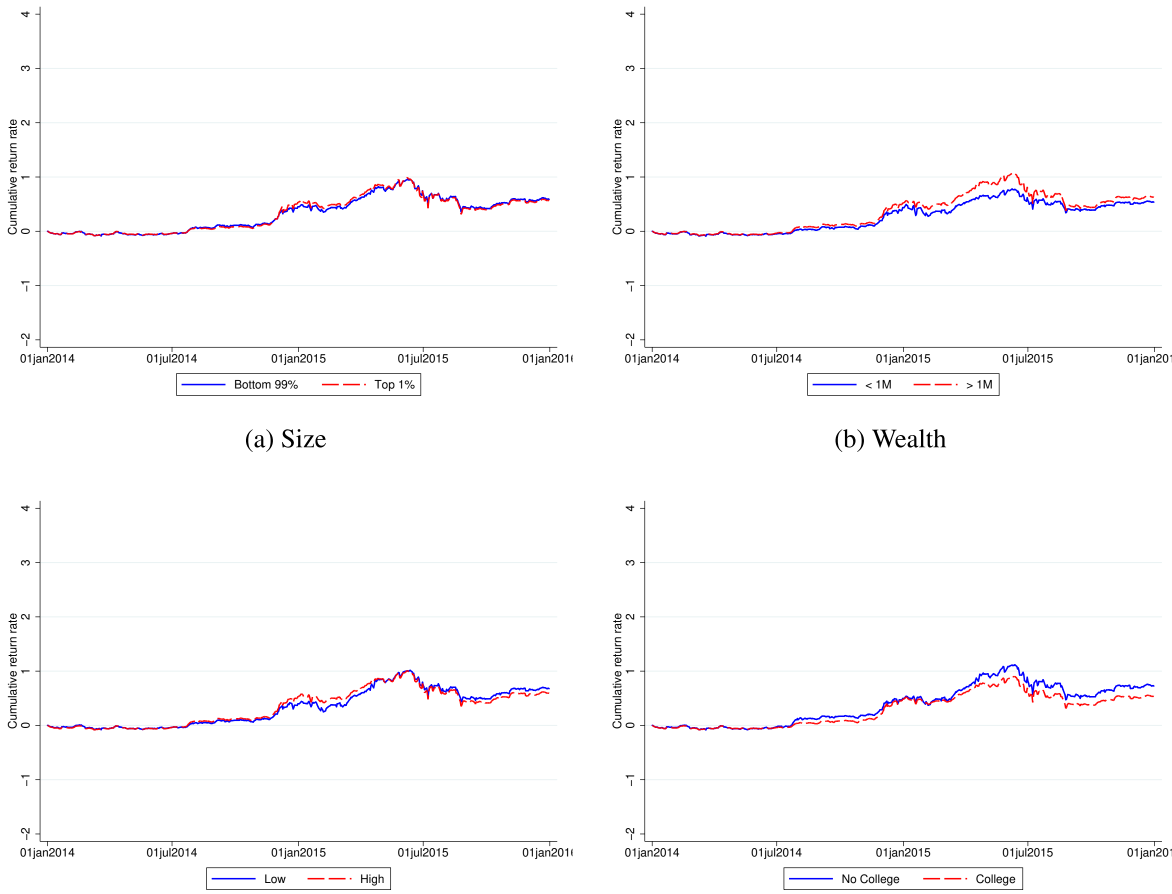

(c) Literacy




(d) Education

Figure 8: ETF RMB Returns for Investor Groups

Note: Cumulative returns from ETFs from 2014 to 2015 for investors of different demographic groups. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth. High financial literacy indicates self-reporting good financial knowledge and practical skills.




(a) Size

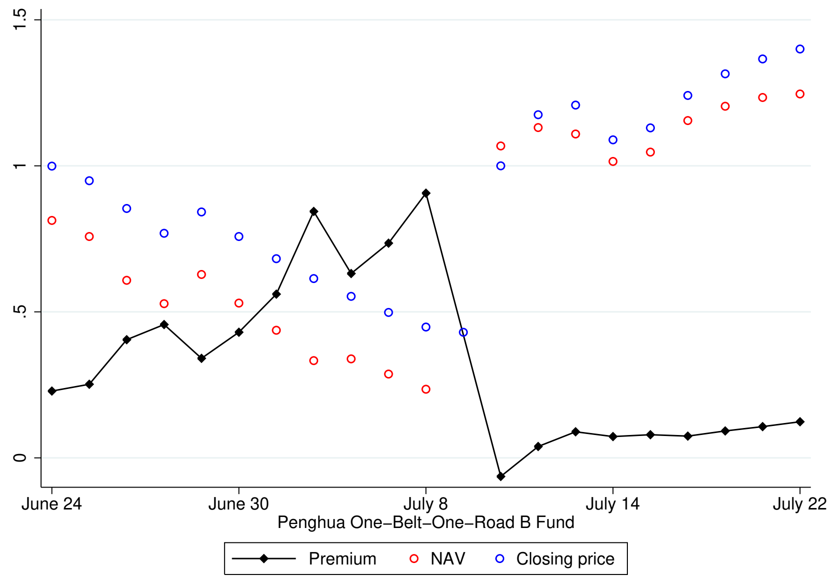
(b) Wealth

(c) Literacy

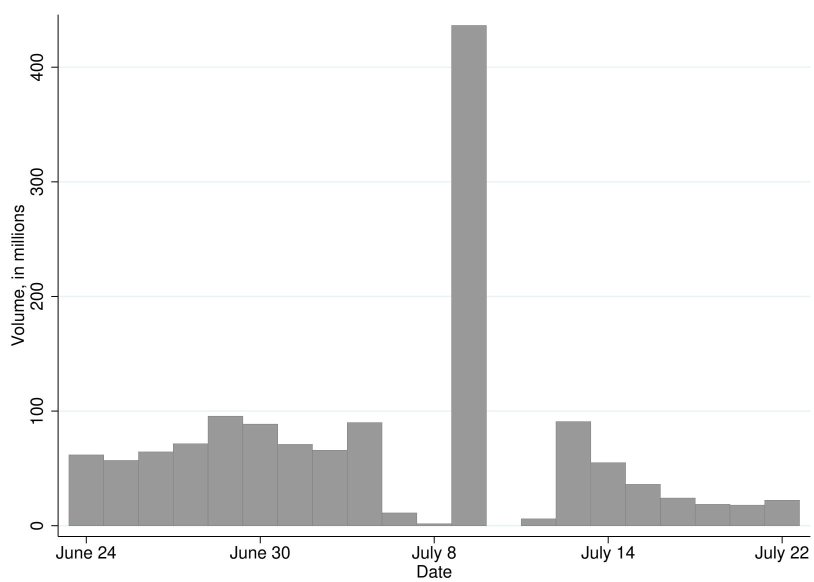
(d) Education

Figure 9: ETF Return Rates for Investor Groups

Note: Cumulative return rates from ETFs from 2014 to 2015 for investors of different demographic groups. Return rates are calculated by dividing RMB return by average daily balance. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth. High financial literacy indicates self-reporting good financial knowledge and practical skills.



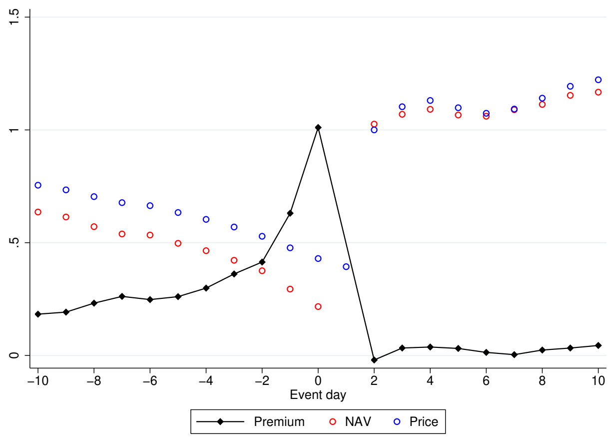

(a) Price and NAV



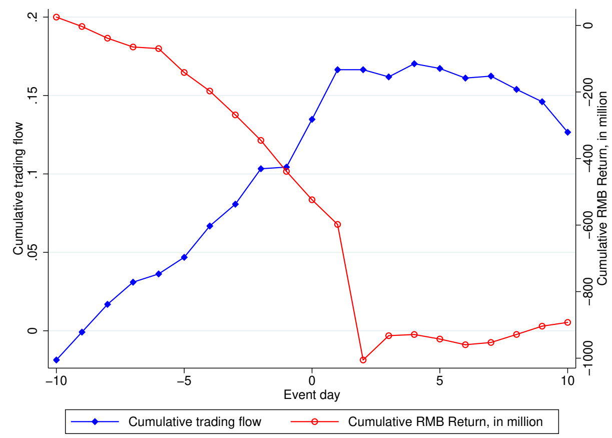

(b) Daily volume

Figure 10: Restructuring Event of Penghua B Fund

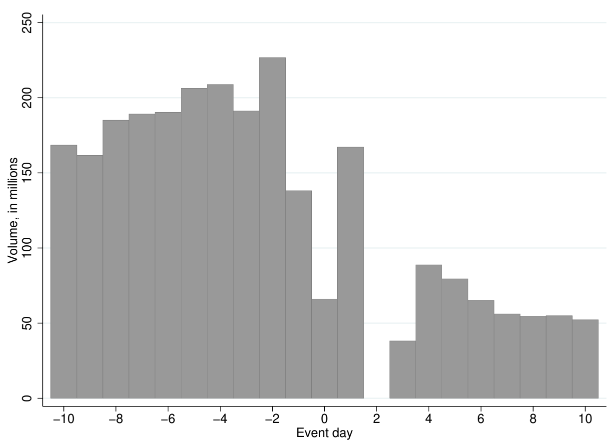
Note: Sub-figure 11 plots the evolution of NAV and price during the 21-day window around the restructuring event for Penghua One-Belt-One-Road Fund. Sub-figure 10b plots the daily trading volume during the same period.



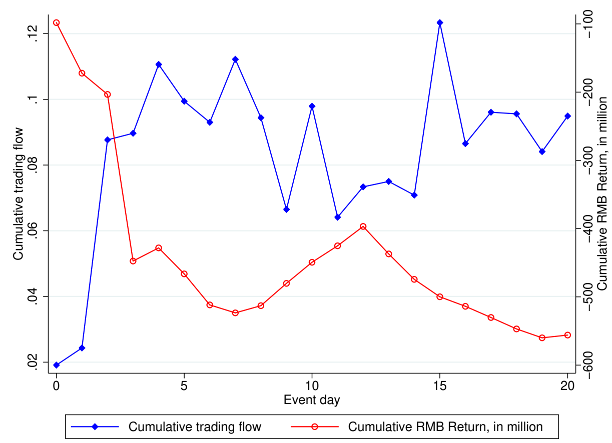

(a) All restructuring events




(b) All restructuring events (NAV < 0.25)



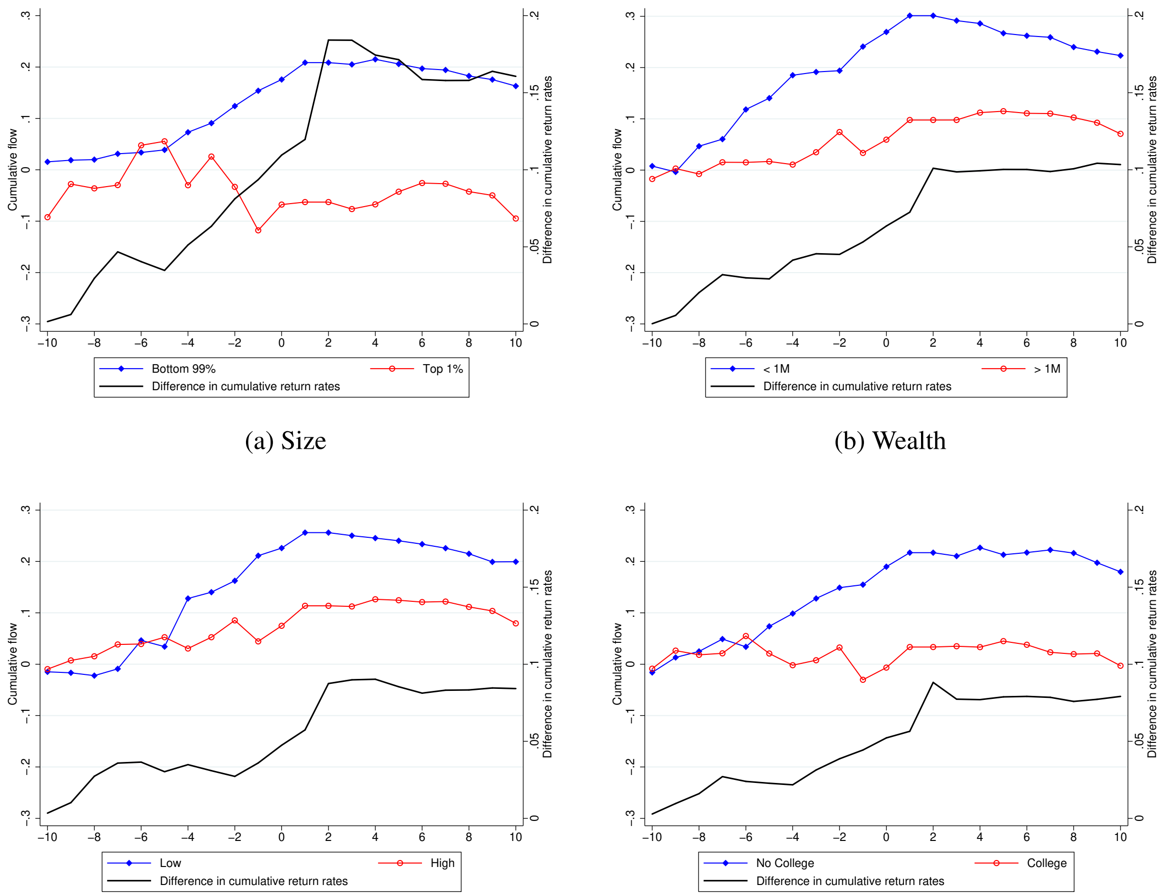

(c) Daily trading volume




(d) NAV < 0.35

Figure 11: B Funds during Restructuring Events

Note: Sub-figure 11a plots the evolution of NAV and price during the 21-day window around the restructuring events. Sub-figure 11b plots the distribution of trading flows around the restructuring events. Trading flow is normalized using the initial account balance. Sub-figure 11c plots the daily trading volume averaged across all restructuring events. For Sub-figures 11a to 11c, day 0 is defined as the first time that a fund's closing price drops below the threshold. Sub-figure 11d plots the post-event trading flows and returns, where the event is defined by the first time a fund drops below 0.35.




(a) Size

(b) Wealth

(c) Literacy

(d) Education

Figure 12: Cumulative Trading Flows during Restructuring Events

Note: Trading flows and return rates around the restructuring event for different demographic groups. Fund flow is normalized using the initial account balance. Return rates are calculated by dividing RMB return by average daily balance. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth. High financial literacy indicates self-reporting good financial knowledge and practical skills.

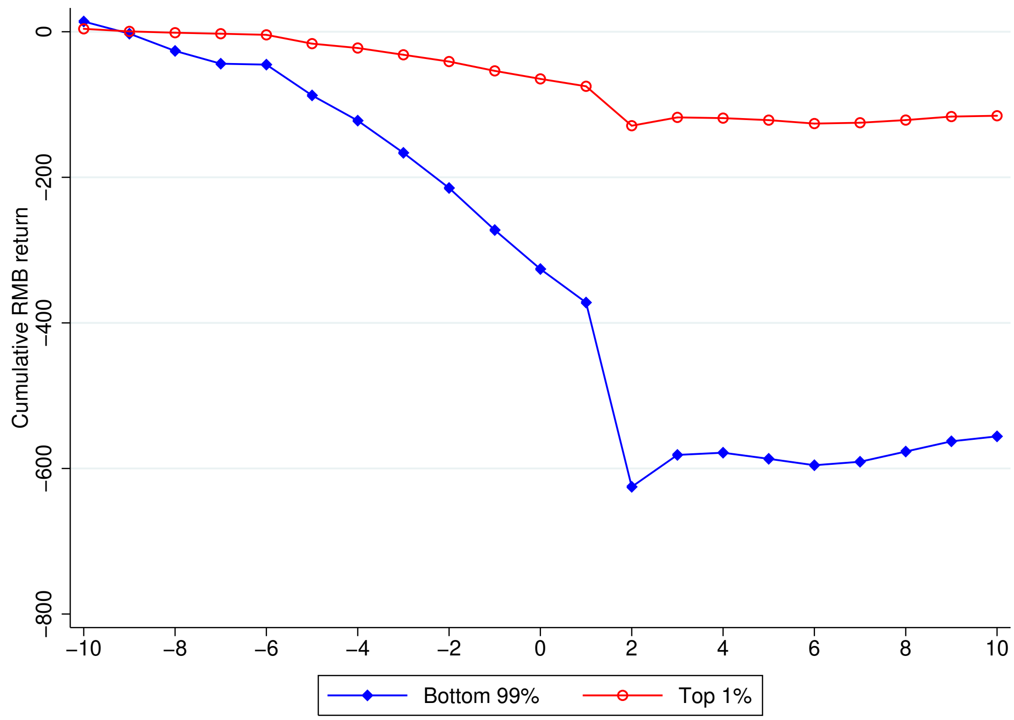
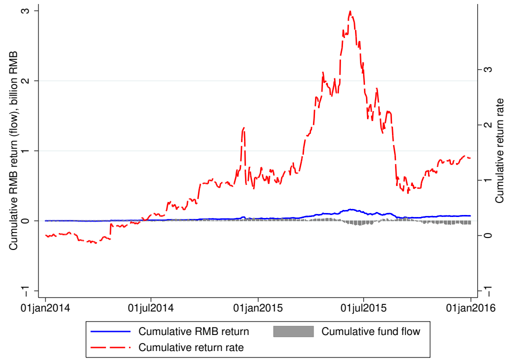
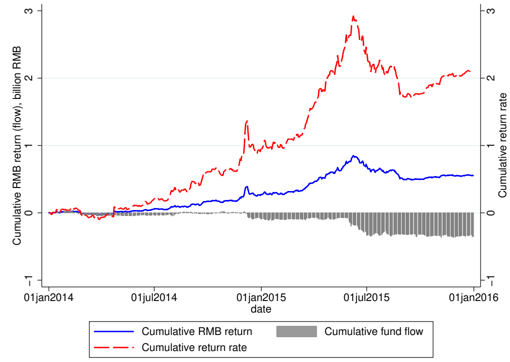



Figure 13: Wealth Redistribution during Restructuring Events

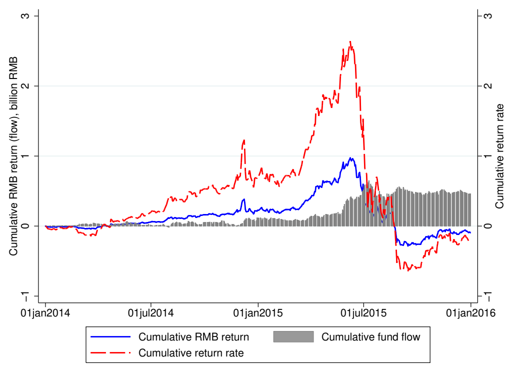
Note: Cumulative RMB returns from B funds during restructuring events. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have a maximum account balance lower than 5 million RMB by the end of 2013.



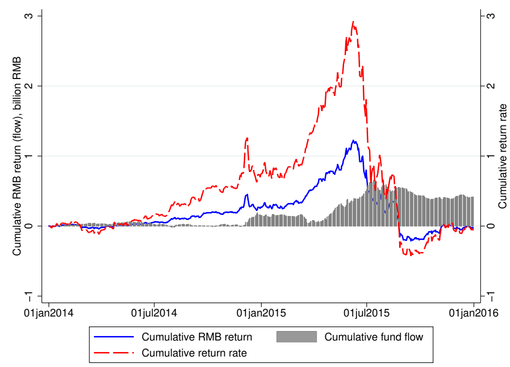

(a) Liquidity providers



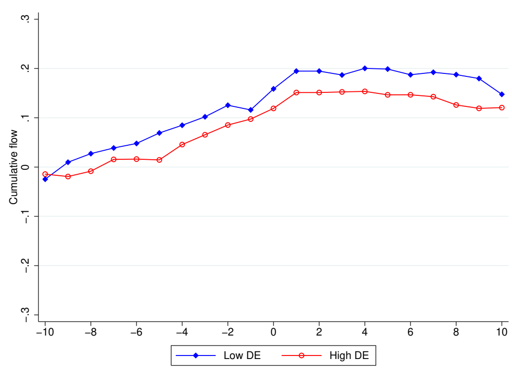

(b) Non-liquidity providers



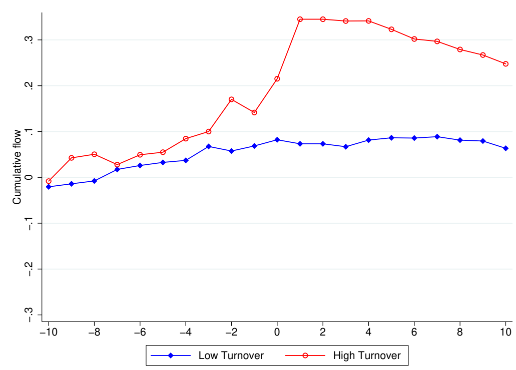

(c) High-disposition




(d) Low-disposition



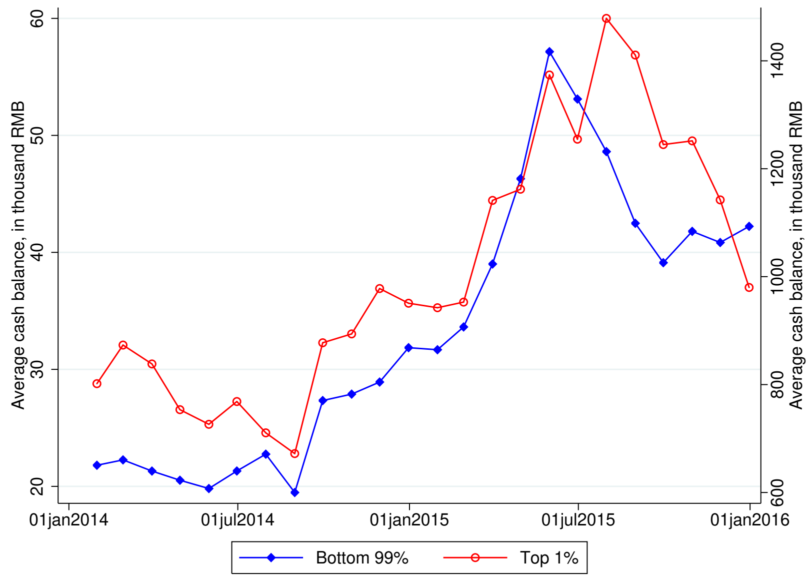

(e) Disposition effect



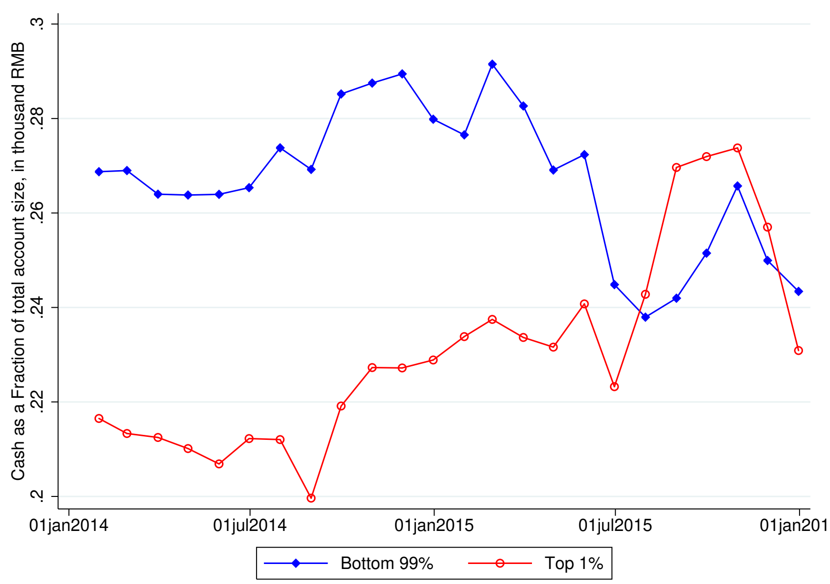

(f) Turnover

Figure 14: Evidence on Alternative Mechanisms

Note: Sub-figures 14a to 14d plot the cumulative returns and flows from B funds from 2014 to 2015 for different investor groups. The blue solid line represents the cumulative RMB return from trading B funds. The grey bar represents the cumulative RMB flow into B funds. Both series are scaled using the left axis. The red dashed line represents cumulative return rate, calculated by cumulative RMB return by average investment calculated based on daily investment. A liquidity provider is defined as a top-1% investor with a positive account balance for at least 120 days and a turnover rate above the median. Other top-1% investors are considered non-liquidity providers. Disposition effect is measured by the difference between the proportion of gains realized and the proportion of losses realized on selling days. A high-disposition investor has a disposition effect above the median. Sub-figures14e and 14f plot the evolution of trading flows around the restructuring event for different investor groups. Trading flow is normalized using the initial account balance. Turnover is measured as the sum of transaction values divided by the average account balance; a high-turnover investor has a turnover rate above the median.



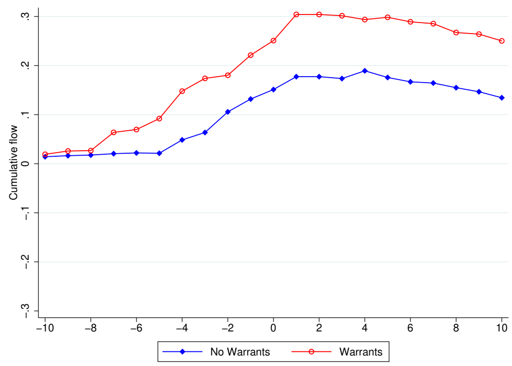

(a) Cash



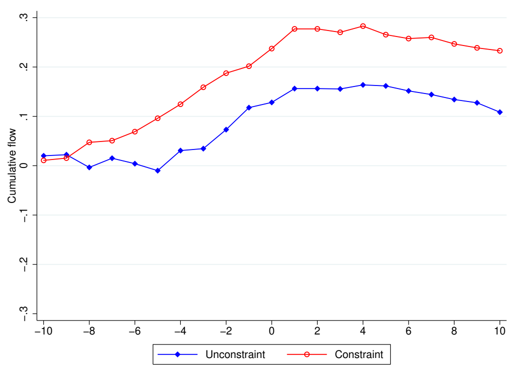

(b) Fraction of cash

Figure 15: Cash Holdings, 2014-2015

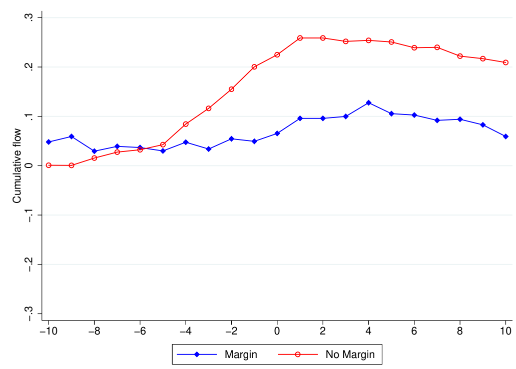
Note: Evolution of cash holdings for different investor groups. In Figure 15a, the left axis represents the bottom-99% investors and the right axis represents the top-1% investors. Cash represents the amount of cash balance in the account. Fraction of cash is calculated by dividing the amount of cash to the total account balance.




(a) Traded warrants before



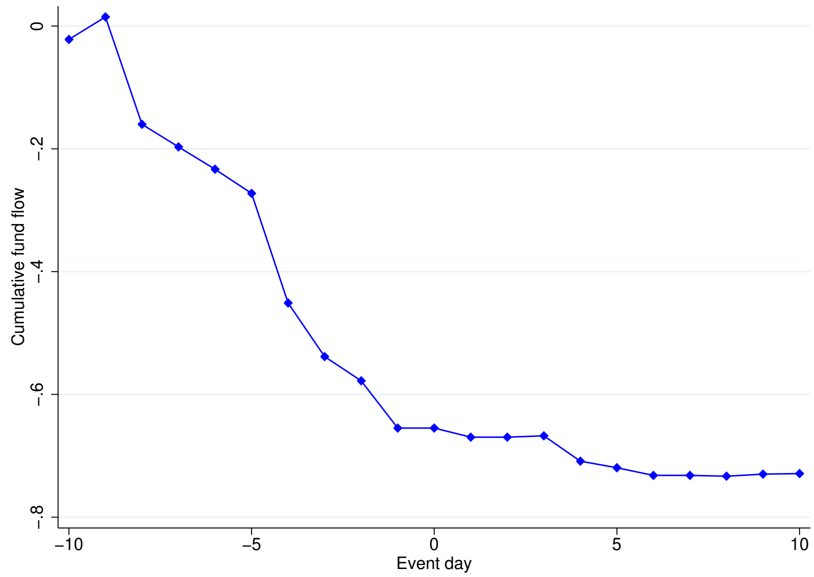

(b) Cash positions



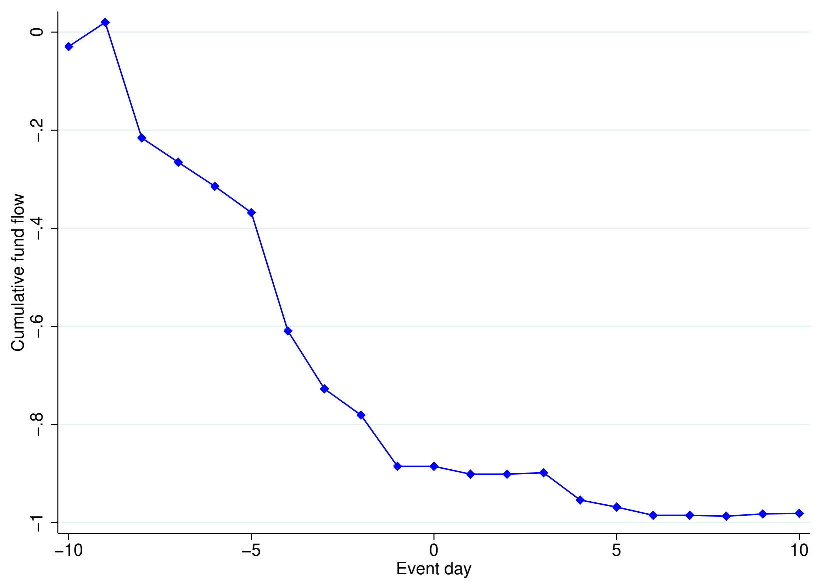

(c) Margin accounts

Figure 16: Comparing Fund Flows among Different Investor Groups

Note: Evolution of trading flows around the restructuring event for different investor groups. Fund flow is normalized using the initial account balance. Disposition effect is measured by the difference between the proportion of gains realized and the proportion of losses realized on selling days. An investor is considered constraint in borrowing if she has less than 10% of her account balance in cash.




(a) All institutional investors




(b) “Active” institutional investors

Figure 17: Institutional Investors during Restructuring Events

Note: Cumulative trading flows for institutional investors during the 21-day window around the restructuring events. An institutional investor must have at least 100 fund-day observations to be included in the analysis. Sub-figure 17a considers all institutional investors. Sub-figure 17b considers “active” institutional investors, who have traded at least 10 times in the sample.

| Industry | Obs. |
|---|---|
| Market index | 42 |
| Energy and engineering | 23 |
| Telecom and information technology | 13 |
| Finance | 12 |
| Healthcare and pharmaceutical | 6 |
| Real estate | 3 |
| Other/missing | 16 |

| NAV threshold | Obs. |
|---|---|
| 0.25 | 109 |
| 0.3 | 1 |
| Other/missing | 5 |

| Interest rate paid to the A tranche | Obs. |
|---|---|
| One-year fixed deposit rate + 3% | 51 |
| One-year fixed deposit rate + 3.5% | 31 |
| One-year fixed deposit rate + 4% | 22 |
| Other/missing | 11 |

| Initial leverage (A:B) | Obs. |
|---|---|
| 1:1 | 107 |
| 1:1.5 | 8 |

Table 1: Summary Statistics of Equity-linked B Funds

Note: Summary statistics for the 115 equity-linked B funds trading in Chinese markets by the end of 2015.

| Month | P10 | P25 | P50 | P75 | P90 | Std. dev. | Mean |
|---|---|---|---|---|---|---|---|
| 2014m1 | 1% | 5% | 23% | 84% | 100% | 39% | 40% |
| 2014m2 | 1% | 5% | 22% | 84% | 100% | 39% | 39% |
| 2014m3 | 1% | 5% | 22% | 86% | 100% | 39% | 39% |
| 2014m4 | 1% | 5% | 22% | 84% | 100% | 39% | 40% |
| 2014m5 | 1% | 5% | 22% | 84% | 100% | 39% | 40% |
| 2014m6 | 1% | 5% | 23% | 84% | 100% | 39% | 40% |
| 2014m7 | 0% | 4% | 23% | 84% | 100% | 39% | 40% |
| 2014m8 | 1% | 4% | 21% | 77% | 100% | 39% | 38% |
| 2014m9 | 0% | 4% | 20% | 77% | 100% | 39% | 38% |
| 2014m10 | 0% | 4% | 20% | 75% | 100% | 38% | 37% |
| 2014m11 | 0% | 4% | 18% | 68% | 100% | 38% | 36% |
| 2014m12 | 1% | 5% | 19% | 60% | 100% | 37% | 35% |
| 2015m1 | 1% | 5% | 17% | 55% | 100% | 36% | 34% |
| 2015m2 | 1% | 4% | 17% | 56% | 100% | 36% | 34% |
| 2015m3 | 1% | 4% | 17% | 52% | 100% | 36% | 33% |
| 2015m4 | 1% | 5% | 16% | 49% | 100% | 35% | 32% |
| 2015m5 | 1% | 5% | 18% | 54% | 100% | 35% | 34% |
| 2015m6 | 1% | 5% | 18% | 52% | 100% | 35% | 33% |
| 2015m7 | 1% | 3% | 13% | 44% | 100% | 35% | 30% |
| 2015m8 | 0% | 2% | 8% | 34% | 100% | 35% | 26% |
| 2015m9 | 0% | 1% | 7% | 31% | 100% | 35% | 25% |
| 2015m10 | 0% | 2% | 9% | 37% | 100% | 36% | 27% |
| 2015m11 | 0% | 2% | 10% | 41% | 100% | 36% | 28% |
| 2015m12 | 0% | 2% | 10% | 40% | 100% | 36% | 28% |
| Total | 1% | 3% | 14% | 51% | 100% | 36% | 32% |

Table 3: Portfolio Weight of B Funds Conditional on Holding

Note: Distribution of the portfolio weight of B funds among investors who held B funds in their month-end portfolios. The portfolio weight of B funds is calculated by dividing the total value of B funds by the total value of equity holdings—which includes all exchange-traded equity products such as individual stocks, ETFs, and AB funds—based on investors' month-end holdings. P10, P25, P50, P75, and P90 correspond to the 10th, 25th, 50th, 75th, and 90th percentiles in the distribution.

| | Average | Std. dev. | P25 | Median | P75 | Obs. |
|---|---|---|---|---|---|---|
| Account balance, in million RMB | 0.84 | 52.00 | 0.06 | 0.17 | 0.51 | 1,164,659 |
| Dummy for margin | 0.06 | 0.24 | 0.00 | 0.00 | 0.00 | 1,164,659 |
| Experience with stocks, in years | 5.36 | 3.53 | 1.00 | 6.25 | 8.58 | 1,164,659 |
| Dummy for warrants | 0.12 | 0.33 | 0.00 | 0.00 | 0.00 | 1,164,659 |
| HHI | 0.59 | 0.20 | 0.44 | 0.59 | 0.75 | 1,164,659 |
| Turnover, monthly | 7.62 | 586.46 | 0.51 | 1.26 | 3.21 | 1,164,659 |
| Return rate | -0.02 | 0.65 | -0.04 | -0.01 | 0.00 | 1,164,659 |

Table 4: Summary Statistics for Active Investor Population

Note: Summary statistics for the active investor population calculated by the end of 2015, where an active investor is defined by having bought at least 10 times and sold at least 10 times. Account balance is the maximum month-end balance in RMB during the investor's transaction history. Dummy for margin is an indicator for having a margin account. Experience with stocks is defined by the number of years since an investor first opened the account. Dummy for warrants is an indicator for having traded warrants before. HHI is the Herfindahl-Hirschman Index, normalized by 10,000, which measures the degree of portfolio diversification. Turnover is calculated by dividing total transaction amount by average account balance. Return rate is calculated by dividing total RMB profit by average account balance in RMB.

| | Panel A: RMB return | | | Panel B: Return rate (maximum balance) | | | Panel C: Return rate (average balance) | | | Panel D: Return rate (maximum investment) | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Quiet | Run-up | Crash | Quiet | Run-up | Crash | Quiet | Run-up | Crash | Quiet | Run-up | Crash |
| P10 | -935 | -2,004 | -61,879 | -6.1% | -7.8% | -86.0% | -9.7% | -11.1% | -219.7% | -4.1% | -4.8% | -72.9% |
| P25 | 5 | -151 | -17,430 | 0.3% | -2.3% | -63.3% | 0.4% | -3.0% | -131.9% | 0.2% | -1.4% | -48.4% |
| P50 | 422 | 244 | -3,338 | 10.1% | 2.5% | -28.6% | 16.7% | 3.4% | -54.3% | 9.0% | 1.5% | -21.6% |
| P75 | 2,886 | 3,033 | -292 | 27.1% | 9.3% | -6.7% | 37.4% | 16.2% | -9.8% | 41.9% | 6.9% | -5.1% |
| P90 | 12,330 | 16,482 | 299 | 34.7% | 20.7% | 3.2% | 52.9% | 43.6% | 4.6% | 63.2% | 18.7% | 2.0% |
| Mean | 11,070 | 16,751 | -31,524 | 12.9% | 5.2% | -35.7% | 20.8% | 11.1% | -79.8% | 21.3% | 6.2% | -28.9% |
| Std. dev. | 312,467 | 818,756 | 184,818 | 16.3% | 14.1% | 34.1% | 29.8% | 28.8% | 87.0% | 27.9% | 18.5% | 28.7% |
| Skewness | 95 | 204 | -29 | 25.9% | 182.0% | -44.1% | 100.9% | 204.0% | -96.6% | 106.2% | 419.6% | -64.3% |
| Obs. | 51,812 | 77,623 | 75,209 | 51,812 | 77,623 | 75,209 | 51,812 | 77,623 | 75,209 | 51,812 | 77,623 | 75,209 |

Table 5: Distribution of B Fund Returns at the Investor Level

Note: Distribution of returns from trading B funds during various stages of the bubble. The run-up period is December 1, 2014 to June 12, 2015; the crash period is June 15, 2015 to September 30, 2015; and the rest is the quiet period. Panel A reports RMB return. Panel B reports return rate calculated by dividing total RMB return by maximum balance. Panel C reports return rate calculated by dividing RMB return by average balance. Panel D reports return rate calculated by dividing RMB return by maximum investment, calculated as the sum of initial investment plus maximum new net investment. P10, P25, P50, P75, and P90 correspond to the 10th, 25th, 50th, 75th, and 90th percentiles in the distribution.

| | Run-up | Crash | Run-up | Crash | Run-up | Crash |
|---|---|---|---|---|---|---|
| Wealth (>1M) | 0.005*** | 0.023*** | | | | |
| | (0.001) | (0.003) | | | | |
| Size (top 1%) | | | 0.021*** | 0.038*** | | |
| | | | (0.005) | (0.013) | | |
| Financial literacy (good) | | | | | 0.009*** | 0.025*** |
| | | | | | (0.001) | (0.003) |
| Constant | 0.057*** | -0.365*** | 0.062*** | -0.367*** | 0.054*** | -0.368*** |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.003) |
| Observations | 47,814 | 40,655 | 51,176 | 45,892 | 47,814 | 40,655 |
| R-squared | 0.000 | 0.001 | 0.000 | 0.000 | 0.001 | 0.001 |
| | Run-up | Crash | Run-up | Crash | Run-up | Crash |
| College | 0.003** | 0.008** | | | | |
| | (0.002) | (0.004) | | | | |
| Female | | | 0.008*** | -0.055*** | | |
| | | | (0.001) | (0.002) | | |
| Experienced with B | | | | | 0.111*** | 0.063*** |
| | | | | | (0.004) | (0.011) |
| Experienced with stocks | | | | | 0.030*** | -0.039*** |
| | | | | | (0.002) | (0.007) |
| Constant | 0.057*** | -0.363*** | 0.048*** | -0.330*** | 0.033*** | -0.415*** |
| | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) | (0.005) |
| Observations | 37,339 | 33,050 | 77,623 | 75,209 | 19,414 | 10,659 |
| R-squared | 0.000 | 0.000 | 0.001 | 0.006 | 0.072 | 0.004 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 6: Regressing B Fund Returns on Demographic Variables

Note: Results of regressing B fund return rate on demographic variables for different stages of the bubble. Return rate is calculated by dividing RMB return by maximum account balance. The run-up period is December 1, 2014 to June 12, 2015 and the crash period is June 15, 2015 to September 30, 2015. Wealth (>1M) is an indicator function for self-reporting wealth greater than 1 million RMB. Size (1%) is an indicator function for having an account size in the top 1% of the distribution, which is around 5 million RMB. Financial literacy (good) is an indicator function for self-reporting good financial knowledge and practical skills. College is an indicator function for having a college degree or higher. Female is an indicator function for female investors. Experienced with B is an indicator function for having started trading B funds before the run-up of the bubble. Experienced with stocks is an indicator function for having started trading stocks before the run-up of the bubble.

| | Panel A: B Fund return rate | | | | Panel B: ETF return rate | | |
|---|---|---|---|---|---|---|---|
| | Run-up | Crash | Crash | Crash | Run-up | Crash | Crash |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Wealth (>1M) | 0.005** | 0.010* | 0.002 | 0.003 | 0.010* | -0.005 | -0.006 |
| | (0.002) | (0.006) | (0.008) | (0.008) | (0.005) | (0.007) | (0.009) |
| Size (top 1%) | 0.017*** | 0.029* | 0.036* | 0.039* | 0.025** | -0.029* | -0.025 |
| | (0.006) | (0.016) | (0.022) | (0.021) | (0.012) | (0.015) | (0.021) |
| Financial literacy (good) | 0.007*** | 0.023*** | 0.023*** | 0.023*** | -0.011* | 0.019*** | 0.015 |
| | (0.003) | (0.006) | (0.008) | (0.008) | (0.006) | (0.007) | (0.010) |
| College | 0.005** | 0.002 | 0.010 | 0.012 | -0.001 | 0.006 | 0.010 |
| | (0.002) | (0.005) | (0.008) | (0.008) | (0.005) | (0.006) | (0.009) |
| Female | 0.008*** | -0.043*** | -0.028*** | -0.028*** | 0.006 | -0.001 | -0.006 |
| | (0.002) | (0.005) | (0.007) | (0.007) | (0.005) | (0.006) | (0.009) |
| Experienced with B | | | 0.047*** | 0.050*** | | | 0.001 |
| | | | (0.009) | (0.008) | | | (0.009) |
| ETF return | | | | 0.436*** | | | |
| | | | | (0.051) | | | |
| Constant | 0.055*** | -0.359*** | -0.432*** | -0.427*** | 0.104*** | -0.127*** | -0.134*** |
| | (0.003) | (0.006) | (0.009) | (0.009) | (0.006) | (0.008) | (0.011) |
| Observations | 20,181 | 17,206 | 8,820 | 8,820 | 3,716 | 3,002 | 1,569 |
| R-squared | 0.002 | 0.006 | 0.008 | 0.016 | 0.003 | 0.004 | 0.004 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 7: Regressing B Fund and ETF Returns on Variables

Note: Results of regressing B fund return rate and ETF return rate on various demographic variables for different stages of the bubble. The run-up period is December 1, 2014 to June 12, 2015 and the crash period is June 15, 2015 to September 30, 2015. Wealth (>1M) is an indicator function for self-reporting wealth greater than 1 million RMB. Size (1%) is an indicator function for having an account size in the top 1% of the distribution, which is around 5 million RMB. Financial literacy (good) is an indicator function for self-reporting good financial knowledge and practical skills. College is an indicator function for having a college degree or higher. Female is an indicator function for female investors. Experienced with B is an indicator function for having started trading B funds before the run-up of the bubble. Experienced with stocks is an indicator function for having started trading stocks before the run-up of the bubble.

| | $Dummy_m^B \times 100$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Market return, in % | 0.091*** | 0.044*** | 0.048*** | 0.057*** |
| | (0.018) | (0.013) | (0.012) | (0.015) |
| Extrapolation | | -0.000 | -0.003 | -0.003 |
| | | (0.008) | (0.006) | (0.006) |
| Market return, in % × Extrapolation | | 0.344*** | 0.288*** | 0.301*** |
| | | (0.067) | (0.061) | (0.062) |
| Have a margin account, dummy | | | 0.002*** | 0.001** |
| | | | (0.001) | (0.001) |
| Experience in stocks | | | -0.001*** | -0.001*** |
| | | | (0.000) | (0.000) |
| Account size, log | | | 0.001*** | 0.001*** |
| | | | (0.000) | (0.000) |
| Traded warrants before | | | 0.003*** | 0.004*** |
| | | | (0.001) | (0.001) |
| Return rate, in % | | | 0.021*** | 0.021*** |
| | | | (0.004) | (0.006) |
| Disposition effect | | | -0.003*** | -0.003** |
| | | | (0.001) | (0.001) |
| Volatility | | | -0.003 | 0.008 |
| | | | (0.011) | (0.012) |
| Skewness | | | 0.001** | 0.000 |
| | | | (0.000) | (0.000) |
| Turnover | | | 0.000*** | 0.000 |
| | | | (0.000) | (0.000) |
| HHI index | | | -0.007*** | -0.008*** |
| | | | (0.002) | (0.002) |
| Survey responses | NO | NO | NO | YES |
| Constant | 0.002 | 0.002 | 0.018*** | 0.022*** |
| | (0.002) | (0.002) | (0.004) | (0.006) |
| Observations | 4,541,691 | 4,541,691 | 4,541,691 | 2,520,409 |
| R-squared | 0.002 | 0.004 | 0.006 | 0.006 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 8: Entry Decisions into B funds

Note: Estimation of a regression of entry decisions into B funds on cumulative account characteristics. $Dummy_m^B$ denotes whether an account trades B in month $m$. We do not consider investors who trade B before month $m$. All columns use observations from 2014:12 to 2015:05. Unless stated otherwise, all account-level regressors use transactions up to month $m-1$ and represent an account's cumulative characteristics. Market return represents the market return in the prior month and is in %. Return rate in % is calculated by dividing RMB return by average RMB balance. Extrapolation, Volatility, and Skewness are constructed as the weighted average, based on purchase sizes, past-one-month return, past-12-months volatility, and past-12-months skewness for all purchases, where volatility and skewness are calculated based on the daily returns. Disposition effect is measured by the different between the proportion of gains realized and the proportion of losses realized on selling days. Turnover is calculated as the sum of transaction values divided by average account balance. Account size is measured by the average account balance in million RMB. HHI is calculated as the sum of the squares of each stock's portfolio weight. Experience in stocks in calculated as the number of years since first trading stocks. Column (4) runs the same regression as Column (3) but adds additional variables from surveys. Additional details of the survey variables are included in the Appendix. Standard errors are clustered at the investor and month levels.

# Online Appendix

# 1. Issuance of Structured Funds

Figure A.1 plots the distribution of structured funds by the month they are introduced. The first structured fund was introduced to the Chinese market in 2009. The market for structured funds grew steadily over the next five years. In the first half of 2015, spurred by the Chinese stock market bubble, the market for structured funds exploded, with dozens of new funds issued.

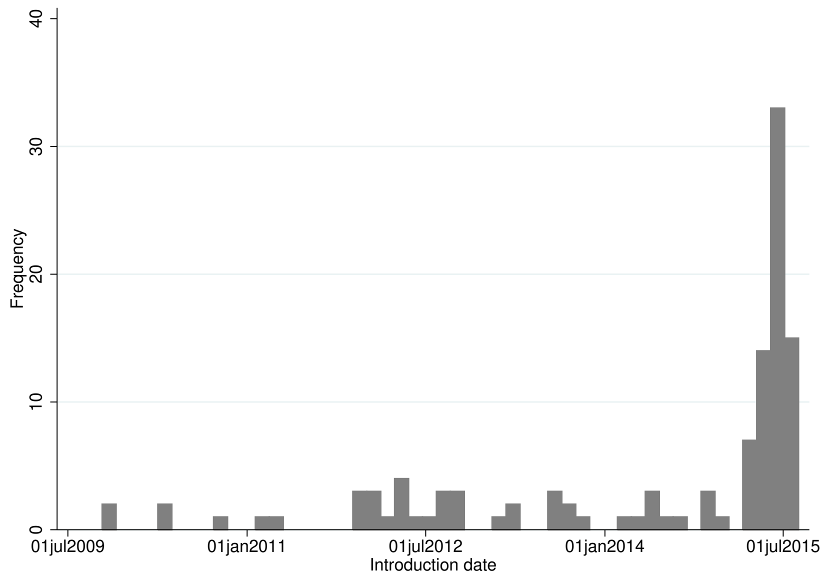



Figure A.1: Issuance of AB funds

Note: Distribution of B funds based on the year they were issued. We only consider B funds linked to an equity index.

# 2. More Details about the Survey Data

Table A.1 reports more details about the survey data. These responses are collected when an investor opens an account for the first time and may therefore be outdated. We translate these questions from Chinese to English; the Chinese version is available upon request.

| Question | Percentage of respondents |
| --- | --- |
| What is your wealth level? | |
| Above 5M | 7.92 |
| Between 1M and 5M | 36.63 |
| Between 500K and 1M | 28.84 |
| Below 500K | 26.62 |
| | |
| What fraction of your wealth is invested in the stock market? | |
| Above 70% | 7.72 |
| Between 30% and 70% | 33.33 |
| Between 10% and 30% | 35.74 |
| Below 10% | 23.21 |
| | |
| What is your annual income? | |
| Above 1M | 6.64 |
| Between 500K and 1M | 23.14 |
| Between 100K and 500K | 41.23 |
| Below 100K | 28.99 |
| | |
| What is your expected return and risk from investment? | |
| Super high return, high risk | 12.89 |
| High return, moderate risk | 48.39 |
| Moderate return, low risk | 31.71 |
| Interest rate, no risk | 7.01 |
| | |
| What is the maximum loss you can tolerate in the next 3 months? | |
| Below 10% | 20.19 |
| Below 20% | 27.30 |
| Below 30% | 37.59 |
| Above 30% | 14.92 |
| | |
| What is the maximum loss you can tolerate in the long run? | |
| Below 20% | 27.86 |
| Below 40% | 31.76 |
| Below 60% | 29.38 |
| Above 60% | 11.00 |
| | |
| What is your investment horizon? | |
| Below 1 year | 14.14 |
| Between 1 year and 3 years | 18.81 |
| Between 3 years and 5 years | 28.77 |
| Above 5 years | 38.28 |
| | |
| How many years of stock market investment do you have? | |
| Below 1 year | 21.48 |
| Between 1 year and 3 years | 16.29 |
| Between 3 years and 5 years | 27.57 |
| Above 5 years | 34.66 |
| | |
| What level of sophistication do you have? | |
| Both knowledge and practice good | 16.48 |
| Knowledge OK, practice good | 39.99 |
| Both OK | 31.30 |
| Both low | 12.23 |

Table A.1: Survey Responses

# 3. Relationship between Leverage and Premium

In Table A.2, Panel A reports the results of regressing fund-level premium on the underlying leverage for all fund-day observations from 2014 to 2016. Column (1) reports the results without any fixed effects. The coefficient is positive and highly significant: a one-unit (one-standard-deviation) increase in leverage is associated with almost a 20% (17%) increase in premium. Moreover, the R-squared is almost 0.56, suggesting leverage alone can account for more than half of the variation in premium. Columns (2) to (4) add different sets of fixed effects and show that the explanatory power of leverage is virtually unchanged. Column (5) adds the squared term of leverage to capture a nonlinear effect: the squared term is positive and significant and the R-squared also increases substantially.

Panel B reports the regression results separately for the three years from 2014 to 2016. The R-squared remains large across the three years, with 2015 having the lowest R-squared—unsurprising given the turbulent market throughout the year. We also notice that the coefficient experiences a gradual decrease, suggesting that with more investors opening margin accounts, there is less demand for levered B funds.

| | Panel A: Pooled regressions | | | | | Panel B: Regressions by year | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (5) | (6) | (7) |
| | 2014-16 | 2014-16 | 2014-16 | 2014-16 | 2014-16 | 2014 | 2015 | 2016 |
| Leverage | 0.190*** | 0.204*** | 0.165*** | 0.184*** | 0.038*** | 0.257*** | 0.183*** | 0.138*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) | (0.001) |
| Leverage$^2$ | | | | | 0.018*** | | | |
| | | | | | (0.000) | | | |
| Time FE | NO | YES | NO | YES | YES | YES | YES | YES |
| Fund FE | NO | NO | YES | YES | YES | YES | YES | YES |
| Constant | -0.188*** | -0.205*** | -0.157*** | -0.180*** | -0.040*** | -0.213*** | -0.118*** | -0.185*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.003) | (0.002) | (0.002) |
| Observations | 56,868 | 56,868 | 56,868 | 56,868 | 56,868 | 9,132 | 20,120 | 27,616 |
| R-squared | 0.558 | 0.695 | 0.734 | 0.838 | 0.883 | 0.978 | 0.635 | 0.879 |

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.2: Regressing B Premium on Leverage

Note: Results of regressing B fund premium on B fund leverage. B premium is calculated as the ratio of the difference between B price and B NAV to B NAV. B leverage is calculated as the ratio of A NAV to B NAV.

# 4. Additional Discussion of Limits to Arbitrage

In theory, there will be an arbitrage opportunity if the total market value of A fund and B fund exceeds the NPV of their parent fund. Since B funds are often persistently traded at a premium, one question naturally arises: why does the law of one price not hold? And what forces limit investors from arbitraging B funds' premium? We argue that limits to arbitrage mainly take two forms in our setting.

The first consideration is the closed-ended nature of B funds. If a mutual fund is traded at a premium, investors can create new shares from the fund family at the cost of NPV and sell them on the secondary market. This, however, cannot be done with B funds. Investors can only create shares of the parent funds and *cannot* directly create new shares of B. As we discussed before, while this can prevent the combined price of A and B shares from deviating too much from the parent fund's value, it does not ensure that each share is correctly priced by itself.

The second consideration is the risks in the "create-split-sell" trade. A typical trade follows the following process: On day $t$, the investor observes that the combined price of A fund and B fund exceeds the parent fund's NPV, so she subscribes to new shares of the parent fund on the primary market before it closes. On day $t+1$, she obtains the new shares of the parent fund after the market closes. On day $t+2$, she splits the parent shares into AB shares, but may not be able to sell them immediately due to regulation. On the Shanghai Stock Exchange, investors can sell immediately on day $t+2$, but on the Shenzhen Stock Exchange—the main exchange for structured funds—immediate selling is not allowed, and our investor would have to wait until day $t+3$. During this three-day period, investors need to bear the risk from noise traders and news on fundamentals, both of which can reduce or even eliminate the profit from the arbitrage trade.

# 5. Alternative Measures of B Return Rates

In Table 6, we use the most conservative return rate by dividing RMB return by maximum account balance. Table A.3 reports the results when we calculate return rate by dividing total RMB return by average account balance. The patterns are similar to those reported in Table 6.

| | Run-up | Crash | Run-up | Crash | Run-up | Crash |
|---|---|---|---|---|---|---|
| Wealth (>1M) | 0.012*** | 0.056*** | | | | |
| | (0.003) | (0.009) | | | | |
| Size (top 1%) | | | 0.045*** | 0.071** | | |
| | | | (0.010) | (0.032) | | |
| Financial literacy (good) | | | | | 0.021*** | 0.055*** |
| | | | | | (0.003) | (0.009) |
| Constant | 0.121*** | -0.826*** | 0.131*** | -0.828*** | 0.115*** | -0.830*** |
| | (0.002) | (0.006) | (0.001) | (0.004) | (0.002) | (0.007) |
| Observations | 47,814 | 40,655 | 51,176 | 45,892 | 47,814 | 40,655 |
| R-squared | 0.000 | 0.001 | 0.000 | 0.000 | 0.001 | 0.001 |

| | Run-up | Crash | Run-up | Crash | Run-up | Crash |
|---|---|---|---|---|---|---|
| College | 0.007** | 0.025*** | | | | |
| | (0.003) | (0.010) | | | | |
| Female | | | 0.010*** | -0.096*** | | |
| | | | (0.002) | (0.006) | | |
| Experienced with B | | | | | 0.240*** | 0.092*** |
| | | | | | (0.007) | (0.030) |
| Experienced with stocks | | | | | 0.065*** | -0.089*** |
| | | | | | (0.004) | (0.018) |
| Constant | 0.119*** | -0.815*** | 0.105*** | -0.750*** | 0.067*** | -0.924*** |
| | (0.002) | (0.006) | (0.001) | (0.004) | (0.003) | (0.012) |
| Observations | 37,339 | 33,050 | 77,623 | 75,209 | 19,414 | 10,659 |
| R-squared | 0.000 | 0.000 | 0.000 | 0.003 | 0.082 | 0.002 |

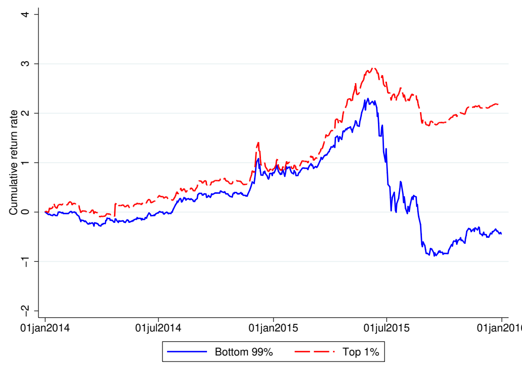
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table A.3: Regressing B Fund Returns on Demographic Variables

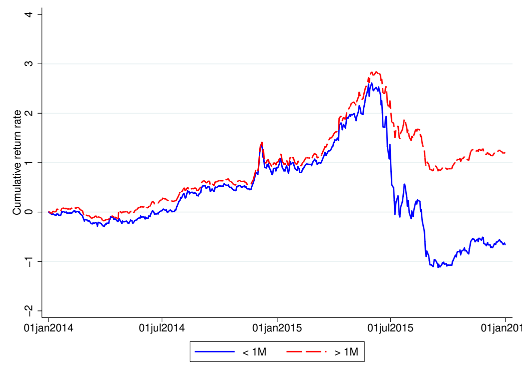
Note: Results of regressing B fund return rate on various demographic variables for different stages of the bubble. Return rate is calculated by dividing RMB return by average account balance. The run-up period is December 1, 2014 to June 12, 2015 and the crash period is June 15, 2015 to September 30, 2015. Wealth (>1M) is an indicator function for self-reporting wealth greater than 1 million RMB. Size (1%) is an indicator function for having an account size in the top 1% of the distribution, which is around 5 million RMB. Financial literacy (good) is an indicator function for self-reporting good financial knowledge and practical skills. College is an indicator function for having a college degree or higher. Female is an indicator function for female investors. Experienced with B is an indicator function for having started trading B funds before the run-up of the bubble. Experienced with stocks is an indicator function for having started trading stocks before the run-up of the bubble.

# 6. Returns for Funds with a Common Index

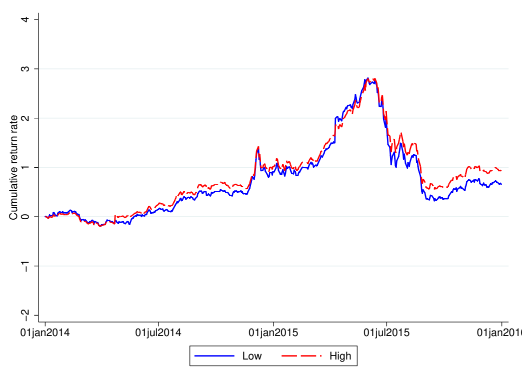
In Section 3, we study the returns for all B funds and all ETFs. In this section, we focus on the subset of B funds and ETFs that share an equity index. Figures A.2 and A.3 plot the return rates from 2014 to 2015. Results for RMB returns are similar to those in Section 3 and are available upon request. The patterns documented before are robust in these subsets of B funds and ETFs. In particular, the difference in return rate is much more pronounced for B fund returns.



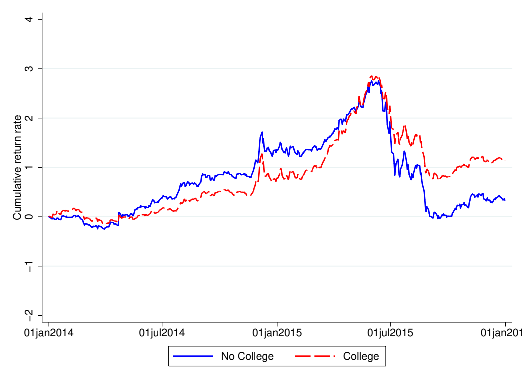

(a) Size




(b) Wealth



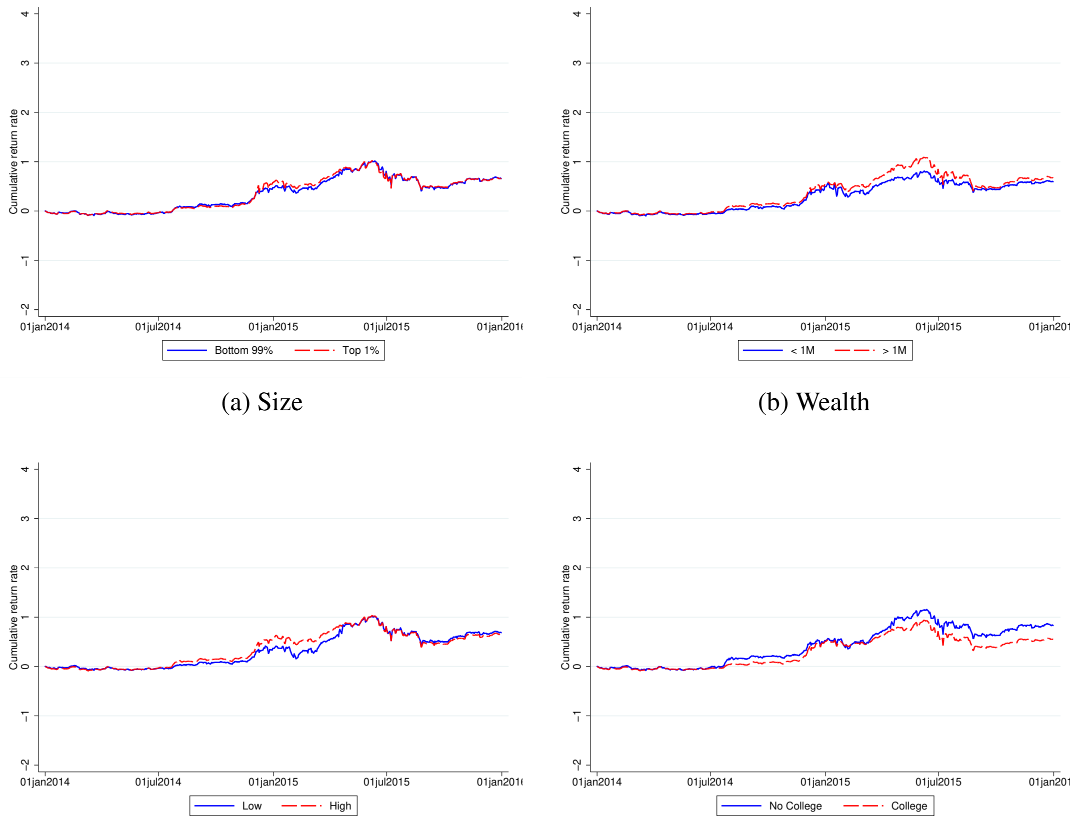

(c) Literacy




(d) Education

Figure A.2: B Return Rates for Investor Groups

Note: Cumulative return rates from B funds from 2014 to 2015 for investors of different demographic groups. A B fund must have its underlying equity index shared with another ETF to be included in the analysis. Return rates are calculated by dividing RMB return by average daily balance. Top-1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom-99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth. High financial literacy indicates self-reporting good financial knowledge and practical skills.




(a) Size

(b) Wealth

(c) Literacy

(d) Education

Figure A.3: ETF Return Rates for Investor Groups

Note: Cumulative return rates from ETFs from 2014 to 2015 for investors of different demographic groups. An ETF must share its underlying equity index with another B fund to be included in the analysis. Return rates are calculated by dividing RMB return by average daily balance. Top-1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom-99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth. High financial literacy indicates self-reporting good financial knowledge and practical skills.

# 7. Distribution of Restructuring Events

Figure A.4 plots the distribution of restructuring events, which are identified when the end-of-the-day NAV of a B fund drops below a prespecified threshold. As Figure A.4 shows, most of the restructuring events occurred during the 2015 Chinese market crash.

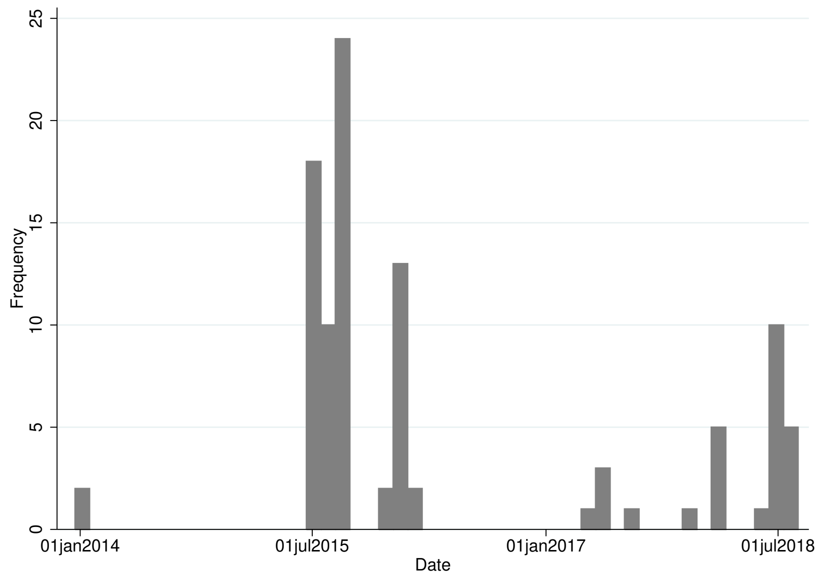



Figure A.4: Distribution of Restructuring Rvents
Note: Distribution of restructuring events from 2013 to 2018. A restructuring event occurs when the pre-share NAV of B falls blow a prespecified threshold.

# 8. More Details about Premium during Restructuring Events

## 8.1 Price limit rule

Institutional frictions in the Chinese stock market also add to the premium of B funds. Specifically, the Chinese stock market has a 10% daily price change limit: a security's daily return cannot exceed positive or negative 10% based on the previous day's closing price. This rule holds for B funds and their underlying assets. If the underlying assets drop by 8% and the B fund has a leverage ratio of 2:1, then the B fund should drop 16%. However, due to the negative 10% price limit, the B fund can only drop 10%, which leads to a 6% premium of the B fund. During the market crash, as in our sample, this mechanical friction may cause a large overpricing of B funds, relative to the NPV of parent funds. However, after restructuring, the new shares will begin trading at the new NAV, which will mechanically eliminate the premium of B funds.

## 8.2 Premium when leverage resets

We provide additional evidence that investors should rationally expect the premium to disappear after restructuring. Specifically, we focus on the sample period from 2014:01 to 2015:06 and narrow our sample to funds with a leverage that is close to 1 and is being actively traded in the market. We examine the distribution of their premiums and report the results in Figure A.5. Both the medium and average premiums are about 7%, consistent with the positive average B premium. However, this is much smaller than the 100% prior to restructuring. Therefore, investors *should* expect the premium to disappear if they are careful enough to study the distribution of premiums in the market. The maximum premium during the whole sample period is around 50%.

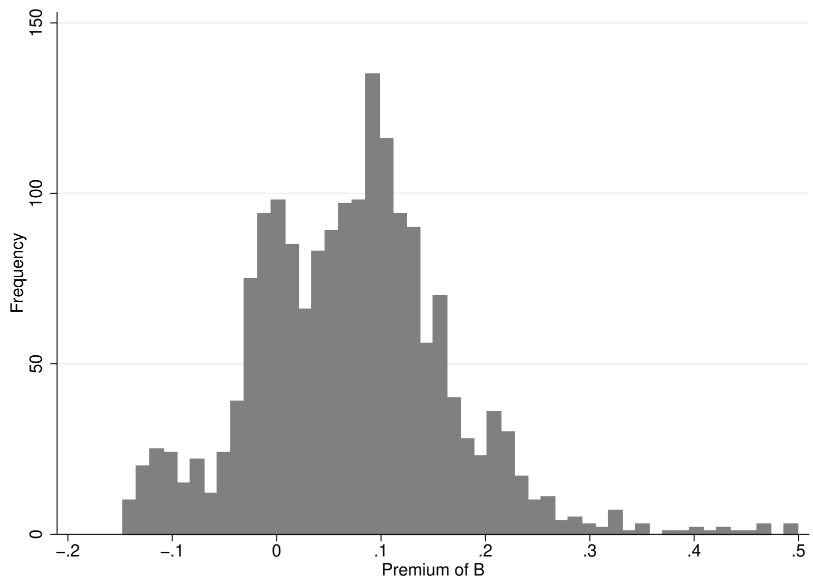



Figure A.5: Distribution of Premium

Note: Distribution of premium for B funds with a leverage between 0.95 and 1.05. All observations are from 2014:01 to 2015:06, prior to the market crash.

# 9. Evidence from Prospectuses

We present additional evidence about the issuers' discussion of risk in their prospectuses. We first download all their initial prospectuses when funds are issued for the first time and perform basic textual analysis on these documents. Table A.4 reports the summary statistics. On average, a prospectus is about 132 pages long and its risk section only starts on page 86. While prospectuses typically talk about premium and restructuring events, only three explicitly talk about the risks associated with restructuring events.

| | # of pages | # of characters | Word count | | | | Risk section | |
|---|---|---|---|---|---|---|---|---|
| | | | "Return" | "Premium" | "Restructure" | "Restructure risk" | First page | Length |
| Mean | 129 | 113,802 | 128 | 4 | 176 | 3 | 86 | 5 |
| Median | 132 | 115,554 | 126 | 4 | 166 | 0 | 89 | 5 |
| Min | 47 | 12,222 | 51 | 0 | 66 | 0 | 0 | 0 |
| P25 | 118 | 104,807 | 112 | 3 | 147 | 0 | 78 | 4 |
| P75 | 146 | 126,157 | 143 | 4 | 193 | 0 | 97 | 6 |
| Max | 199 | 153,239 | 371 | 11 | 328 | 1 | 149 | 8 |
| Std. dev. | 24 | 17,980 | 32 | 1 | 46 | 0 | 21 | 2 |

Table A.4: Summary Statistics of Prospectuses

# 10. Variable Definitions

Table A.5 defines the variables used in Section 5.

| Characteristic | Description |
|---|---|
| Extrapolation | Weighted-average past-1-month return for all purchases |
| Volatility | Weighted-average past-12-months volatility for all purchases |
| Skewness | Weighted-average past-12-months skewness for all purchases |
| Disposition effect | Proportion of gains realized minus proportion of losses realized |
| Turnover | Sum of transaction values divided by average account balance |
| HHI | Sum of the squares of each portfolio's weight |

Table A.5: Definitions of Investor Characteristics