# Exploited by Complexity

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**Abstract**

Fee-based brokers of complex retail products are incentivized to exploit naive households by selling them inferior products. In a setting of exchange-traded structured funds, we show that, even without the influence of fee-based brokers, naive investors are harmed by investing in complex financial products. By contrast, sophisticated investors benefit from the same products. The resulting difference in returns is an order-of-magnitude greater than the return difference from trading simple, non-structured funds. In an event study, we further demonstrate that this disparity is driven by differences in investors' understanding of product complexity. When a market crash triggers the funds into a restructuring process and significant loss of value, naive investors respond less rationally than their sophisticated counterparts.

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# 1 Introduction

The market for retail structured financial products has experienced remarkable growth in Europe and is rapidly expanding in the US and Asia.[1] A recent literature examines the design of structured products and argues that their complex features and fee structures create perverse incentives for brokers to sell clearly inferior products to households (Bordalo et al. 2016; Egan 2019; Egan et al. 2019). Consistent with this exploitation-based view, issuers market these products to potential buyers by intentionally shrouding the products' negative attributes while highlighting their positive ones (Célérier and Vallée 2017). Households are misled to ignore or dismiss the shrouded negative features of a product, and ultimately earn negative risk-adjusted returns (Henderson and Pearson 2011; Vokata 2020).

Ideal regulation should provide access to these popular structured products while preventing exploitation by brokers (Campbell 2016). One solution is to reduce the interaction between brokers and households by enlarging the set of structured products available on the exchange. Exchange-traded structured products offer direct access to households and avoid the incentive problems with brokers induced by the fee restructure, potentially eliminating the need for onerous regulation. For example, as more leveraged exchange-traded funds (ETFs) and notes (ETNs) become available, retail investors gain increased access to leveraged products without the need to rely on brokers.

In this paper, we argue that the elimination of broker influence does not solve the problem of exploitation in the market for complex financial products. We conjecture that, instead of being exploited by brokers, naive investors who trade complex exchange-traded products will be exploited by the products themselves. Sophisticated investors, by contrast, benefit from complexity. The resulting wealth transfer from naive investors to sophisticated investors will be greater than when products are simple and nonstructured. This conjecture builds on two results from the existing literature. First, households exhibit substantial heterogeneity in their skills when making portfolio decisions, leading to different returns (e.g., Calvet et al. 2007; Grinblatt et al. 2012; An et al.

[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 2020). Globally, the market for retail structured products reached about 1.92 trillion in assets under management in 2016 (Shin 2019).

2019). While most households are naive, some are sophisticated, creating an asymmetry that leads to possible cross-subsidization. Second, the behavioral industrial organization literature suggests that, when both naive investors ("naifs") and sophisticated investors ("sophisticates") are present in a market, product complexity results in a disparity that effectively subsidizes sophisticates while taxing naifs (Ellison 2005; Campbell 2006; Gabaix and Laibson 2006). This, in turn, exacerbates cross-subsidization.

Consider the following example. When introducing a new financial product, issuers are incentivized to highlight its upsides (e.g. cheap leverage) and underplay its downsides (e.g. crash risk). As a result, all investors are equally informed of the product's upsides, but only the sophisticates can sift through complex details to recognize its downsides. When investors begin trading the product on the secondary market, both the sophisticates and the naifs can normally enjoy its positive features by levering up their positions. However, when the market has frictions or investors are less than fully rational, crash risk may rise sharply without immediately impacting the product's price. The sophisticates, knowing that the product is now overpriced, will quickly sell it. The naifs, unaware of the heightened crash risk, will continue to hold the product or even buy more of it, eventually bearing most of the crash risk. Complexity hurts the naifs by subjecting them to risks they are not aware of and worsening their investment performance.

In this paper, we document and study a cross-subsidization from naifs to sophisticates when trading AB funds—structured funds in the Chinese market. AB funds are designed by slicing the payoffs of a regular fund into two tranches: a fixed-income tranche ("A fund") and a levered-equity tranche ("B fund"). In essence, B fund investors are financed by A fund investors to take a levered position in the original fund.[2] For Chinese retail investors, the majority of whom cannot open a margin account, B funds have a clear *upside*: cheap and convenient leverage. By the 2015 market peak, B funds had become immensely popular. Fueled by the rising stock market, they were at one point traded by almost 10% of the active investor population. However, B funds also contain a hidden *downside*: they can experience sudden and substantial drops in value due to embedded restructuring clauses—a complex feature that most investors fail to understand. B funds are well-suited for studying the effects of complexity because of their popularity, salient upsides,

[2]AB funds are structured similarly to the primes and scores introduced to the US market in the 1980s (Jarrow and O'Hara 1989), and to mortgage-based securities (MBSs), popular instruments prior to the financial crisis of 2007–08 (Ghent et al. 2017).

and shrouded downsides.

We obtain complete transaction records of all exchange-traded products for almost three million Chinese investors. We supplement these records with survey-based information on investor wealth, education, and financial literacy. Retail investors constitute the vast majority of our data set, but we also observe a small number of institutional investors. We study investor trading behavior and performance in B funds from 2014 to 2016. Though limited in duration, this three-year window covers a full market cycle—a boom, a bust, and a recovery—allowing us to examine how investors behave under different market conditions. By focusing on exchange-traded products, we limit the effect of any broker incentives to target naive households, as brokers do not receive extra compensation for selling exchange-traded products.

Our first set of results shows that B fund returns are unevenly distributed between the sophisticated and unsophisticated. Using wealth as a proxy for sophistication (Campbell 2006; Calvet et al. 2007; Campbell et al. 2019; An et al. 2019), we classify investors into two groups—top 1% and bottom 99%—based on their total investment size. During the market boom, both groups took advantage of leverage, each making a cumulative profit of around 1 billion RMB at a rate more than doubling the market return. When the market crashed, however, the groups' return profiles began to diverge. By the end of the crash, the top 1% were up about 500 million RMB while the bottom 99% were down by the same amount, implying a 500 million RMB wealth transfer from the bottom 99% investors to the top 1% investors.[3] These results, when applied to the entire investor population, suggest a total wealth transfer of 10 billion RMB. We find similar effects when classifying investors by self-reported wealth and when analyzing alternative measures of returns. We document similar wealth transfers, albeit smaller in magnitude, using education and self-reported financial literacy as other proxies for sophistication.

While it is unsurprising that an asymmetry in financial sophistication leads to a gap in investment performance, we show that the investment performance gap is much greater when investors trade complex products. Complex products provide more opportunities for sophisticated investors to benefit from their superior investment skills at the expense of unsophisticated investors. By contrast, consider an extreme case in which investors are only allowed to trade market index funds. If

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

so, differences in returns would stem solely from different market timing abilities, and knowledge about product features would matter little to returns. Therefore, differences in investment returns are not solely driven by financial sophistication, but also by the set of assets available to investors.

We run multiple tests to quantify the wealth transfer attributable to B funds' complex features. First, we examine investment performance in nonstructured funds—namely simple ETFs. Many B funds and simple ETFs are designed to trace the same index with almost identical underlying assets. However, we find little evidence of a wealth transfer across investor groups in the case of ETF trades. Even when one group outperformed, the return difference was an order-of-magnitude smaller than the return difference seen in trading B funds. This contrast suggests that most of the 10-billion wealth transfer is driven by B funds' complex features.

Second, using an event study, we establish a direct link between the wealth transfer and the complex features of B funds. The event we consider is the restructuring of B fund payoffs following large changes in net asset value (NAV). To establish the validity of the event study, we first document three stylized facts about B funds: 1) on average, they trade at a premium (i.e., at a price higher than the NAV); 2) the premium is time-varying; and 3) the size of the premium is largely determined by the embedded leverage. If leverage were to experience a sudden drop (e.g., a reset), one should *rationally* expect the premium to shrink immediately.

While variation in leverage is mostly determined by market movements, a restructuring clause can reset leverage *by force* when B's NAV drops below a prespecified threshold. The threshold is typically set at such a low level that resets should rarely occur, but in 2015 a market crash triggered a restructuring process for almost half of the existing B funds. Immediately before restructuring, these funds, with an average leverage ratio of 4:1, were trading at a 100% premium. After leverage reset, the premium dropped to essentially zero—due to both the disappearance of the leverage premium and trading rules imposed by the exchange—and the price subsequently fell by 50%. Without taking any actions, investors would find their B fund positions halved in value. Therefore, when the NAV gradually approached the threshold, the dominant strategy was to start pulling money out from B funds and avoid the eventual loss in value caused by restructuring. In fact, even after restructuring was triggered, trading continued for an additional day, giving traders ample time to respond to the event. At this point—regardless of risk preferences or beliefs—investors should have liquidated their B fund positions.

While restructuring clauses are explicitly stated in prospectuses, they are complex and not easy to understand. As a result, unsophisticated investors may have an incomplete understanding of restructuring events, causing them to make suboptimal decisions. Indeed, most investors failed to trade in the right direction in response to restructuring events: overall, they *increased* their B fund holdings by almost 15% in the 11-day window before restructuring was triggered, clearly ignoring the heightened downside risk. In addition to losing 600 million RMB prior to restructuring, they lost another 400 million RMB after restructuring became effective. In contrast, a small set of sophisticated investors did much better. Overall, 25% to 45% of the total wealth transfer can be directly explained by investors' different responses to restructuring events.

We argue that sophisticated investors performed better during these episodes because they understood the product better.[4] Consistent with this explanation, the increase of B fund holdings prior to restructuring was more pronounced in the earlier waves of restructuring events when naive investors had little knowledge about restructuring events. Moreover, in the later waves, investors who held when prior restructuring events took place performed substantially better, suggesting that they learned from past mistakes. We further discuss and rule out a host of alternative explanations based on rational gambling, heterogeneous risk preferences, heterogeneous beliefs, liquidity provision, liquidity shocks, reluctance to realize losses, and inattention.

Finally, we show that investors bought B funds because of their high returns during the market boom. Most new investors were extrapolators who entered soon after the market experienced a large positive return (Shin 2019). Therefore, 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, in a way described by Bordalo et al. (2016).

Our paper contributes to the empirical literature on the welfare implications of retail structured products (Henderson and Pearson 2011; Chang et al. 2015; Célérier and Vallée 2017; Calvet et al. 2020; Vokata 2020). Unlike earlier papers, which focus on the average effect and the interplay between investors and brokers, we study heterogeneous effects and redistributional consequences in a setting devoid of broker incentives. Our key contribution is to show that, even in a setting with-

[4]Various sources can contribute to this better understanding. It could be because they personally understood the product's features better, or received better advice elsewhere regarding how to navigate the contract.

out perverse incentives from brokers, complex products can still harm naive households. Instead of being exploited by brokers, naive households are exploited by the complexity of the products themselves. This evidence also complements a recent literature that studies financial regulation through the lens of advisor misconduct (Egan 2019; Egan et al. 2019; Bhattacharya et al. 2020).

In the context of Chinese markets, several papers have used the introduction of warrants between 2005 and 2008 to study complex securities (Xiong and Yu 2011; Pearson et al. 2020; Li et al. 2020). The closest to ours is Li et al. (2020) who document performance heterogeneity among warrant traders and attribute the outperformance of large traders to liquidity provision. Our paper is distinct in three aspects. First, we provide evidence that the source of performance differences is heterogeneity in product understanding; we find no evidence of liquidity provision playing a role in our setting. Second, by comparing structured funds with simple ETFs, we are able to focus on the role of complexity in explaining performance heterogeneity. Third, we quantify the impact of complexity: we not only demonstrate the magnitude of the wealth transfer, but also directly quantify the effect of complexity through an event study.

Our results offer a cautionary tale to policymakers about the unintended consequences of financial innovation. While the introduction of new, complex products helps complete the market and should improve investor welfare in theory (Allen et al. 1994; Duffie and Rahi 1995), it may also encourage more speculation and lead to even worse investment decisions. The introduction of Chinese structured funds was to fill the void of leveraged products, and the restructuring clauses were put in place with good reason. However, once introduced, investors used these products to make speculative trades without knowing much about their features.[5] Our results offers a particularly important lesson for products with unrealized crash risk.[6] The exchange-traded setting is also pertinent to markets experiencing an expanding pool of complex assets trading on the exchange.[7]

There are some limitations to note about our analysis. We suspect that the introduction of other complex products may have similar effects. However, given the wide range of structured financial products, our results may not apply to all exchange-traded retail structured products.

[5]Following this episode, the Chinese regulators halted the issuance of new structured funds and placed a higher barrier to entry, largely due the negative consequences documented in this paper.

[6]When trading these products, investors may judge the riskiness of an asset based on its history, not by the underlying structure indicated in the prospectus. Therefore, regulators should pay particularly close attention to products with high embedded riskiness, but without a history of high realized volatility.

[7]During the COVID-19 pandemic, leveraged ETNs in the US market anecdotally contributed to personal bankruptcies ("Individual Investors Get Burned by Collapse of Complex Securities," *The Wall Street Journal*, June 1, 2020).

For products that are more (less) complex than retail structured funds, we conjecture—but do not show—that the scale of the associated wealth transfer could be greater (lower). Second, although losses were substantial conditional on participation, high levels of non-participation imply a small unconditional effect on the average investor.

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: payoffs of a regular mutual fund ("parent fund"), often linked to a bond or equity index, are sliced into two tranches, a dividend-based tranche ("A fund") and an appreciation-based tranche ("B fund"). Shares are then issued for each tranche with the initial net asset value (NAV) normalized to one per share. A shares receive interest (dividend) payments according to a prespecified interest rate, which means that the NAV is well defined and not affected by price fluctuations in the underlying assets. B shares have the residual claim—that is, the difference in the NAV between parent shares and A shares—and are therefore very sensitive to price movement in the underlying assets. Essentially, B investors take a levered position in parent shares by borrowing from A investors at the interest rate.

Similar to standard mutual fund shares, parent shares can be created or redeemed at the NAV through brokers and are typically *not* traded on the exchange.[8] In contrast, A and B shares are traded on the exchange and cannot be directly created or redeemed through brokers. As a result,

[8] A dozen parent funds are listed on the Shanghai Stock Exchange. The main exchange for structured funds, the Shenzhen Stock Exchange, prohibits parent funds from listing on the secondary market.

the standard arbitrage mechanism through creation and redemption is not at work.[9] Instead, the main arbitrage mechanism—the so-called "create-to-split-and-sell" trade—involves the conversion of shares between the parent and the two tranches. For example, when both A and B are trading at a premium, the arbitrageur would need to (i) create new parent shares through the broker, (ii) split these parent shares into A and B shares, and (iii) sell them on the exchange; a reverse trade applies when A and B shares are both trading at a discount.

There are two significant limitations to this arbitrage mechanism. First, each of the three steps is subject to various trading rules and the entire process takes at least two days to complete. Because of the time it takes, arbitrage has various risks, especially when the market is volatile (Shleifer and Vishny 1997). Second, while the arbitrage 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. If A shares are trading at a discount and B shares at a premium, but their combined price equals the parent's value, the above arbitrage trade will not make a profit. Indeed, as we demonstrate later, there was persistent mispricing in the market of AB funds. Given these limits to arbitrage, B funds can be conveniently thought of as similar to levered closed-end funds.

Trading from retail investors concentrated on the equity-linked B funds, to which the bulk of our subsequent analysis is devoted. There were 115 equity-linked B funds by the end of 2015, and their characteristics are summarized 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. The average interest rate was 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 similar NAV threshold of 0.25 as the trigger for restructuring events, which we explain in greater detail below.

## 2.2 Complex features of B funds

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.

[9] If an ETF is trading at a premium, arbitrageurs can trade it away 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.

### 2.2.1 Feature I: time-varying leverage

Unlike a standard levered fund, which rebalances 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 A shares and 100 B shares, all at the per-share NAV of one. Assume an annual interest rate of 8% with the first payment paid made right *after* month 12. Table 2 shows how changes in P's NAV affect the embedded leverage. When P rises in value, B also rises in value, reducing leverage; conversely, when P drops in value, B also drops in value, increasing leverage. This feature of time-varying leverage poses a first layer of complexity for retail investors. To keep leverage at a constant level, they would need to rebalance portfolios on their own on rather than delegate the task to fund managers.

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

Table 2: An example of the payoff structure for structured funds

### 2.2.2 Feature II: restructuring clauses

A second layer of complexity stems from the inclusion of restructuring clauses. Without putting in any extra clauses, the A tranche is not risk-free: if the parent's NAV drops by more than 50%, the loss will start to affect the NAV of the A tranche as the B tranche becomes worthless. 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, putting the A tranche on the edge of losses. To ensure 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.[10] 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.

[10]Similar restructuring events are triggered when the per-share NAV of the parent fund rises above a certain threshold (1.5 or 2 RMB for most funds). However, these events happen rather infrequently and their wealth implications are much less significant.

During restructuring, the number of shares is cut short for both tranches so that their per-share NAVs are reset to one. For example, in Table 2, when the per-share NAV of P falls to 0.65, 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 one. To adjust the leverage ratio back to 1:1, the number of A shares will also be reduced to 22, and the residual value ($1.08 \times 100 - 1 \times 22 = 86$) will be converted back into 86 shares of P. In practice, these extra parent shares can be immediately cashed out at the broker. Therefore, after restructuring, 78 A shares and 78 B shares are extinguished, NAVs are reset to one, and A share holders are compensated with extra parent shares so that they do not experience any losses, at least in terms of NAV. We explain the timeline of restructuring events in greater detail in Section 4.

### 2.2.3 Comparison with other structured products

Previous studies of retail financial markets show that the fee structure can encourage exploitation. Because brokers are compensated more for selling inferior products, they choose naive households as the target. In our setting of exchange-traded funds, however, such perverse incentives are largely mitigated. Brokers get compensated simply by transaction fees—the fee is comparable to the fee for trading individual stocks—not by kickbacks from issuers. Issuers charge management fees, typically around 1% annually.

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 2020), 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.[11] 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. Previous studies mostly analyze the interaction

[11] 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 2020); private-label mortgage-backed securities have complicated waterfall structures (Ghent et al. 2017).

between brokers and households in markets for illiquid financial products. Due to brokers' market power and screening mechanism, complex products are likely to be sold to less-sophisticated investors over the counter (Egan 2019; Vokata 2020). 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 the same product. More importantly, unlike some settings in which the fee structure creates incentives for brokers to sell inferior products to households, brokers in our setting charge a flat fee rate to all exchange-traded funds and stocks. 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.

## 2.3 B funds during the bubble

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

### 2.3.1 Market size

For a financial product to have a material impact on a household's financial wealth, it should at least constitute a sizable part of the 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, many new AB funds were issued and their total assets under management (AUM) reached 350 billion RMB—almost 10% of the entire mutual fund industry and comparable in scale to the ETF market.[12] Table 3 shows the monthly distribution of B funds' portfolio weight among investors with a positive balance of B

[12] See Section 1 in the Online 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.

shares. For an average (median) investor, B funds constituted 32% (14%) of her equity holding.[13] In fact, more than 10% of B investors were holding only B funds in their equity accounts. While only 12% of the active investors were ever invested in this asset class, the conditional stake was rather high.

### 2.3.2 Complex features

**Time-varying leverage.** Retail investors in the Chinese stock market were highly subject to leverage constraints (Bian et al. 2021). 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.[14] Third, the exchange-traded feature made B funds highly liquid and easily accessible to small retail investors.

Likely as a result of this "cheap leverage" feature, B funds became exceedingly overpriced in 2015. Figure 2 plots the time-series of the leverage and premium averaged across all B funds in 2015. In the first few months when the market was rising, B's leverage dropped and the associated premium declined. 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.

The strong relationship between leverage and premium holds not only in time-series but also in the cross-section of funds: funds with a higher leverage were associated with a higher premium. We present the cross-sectional evidence in Section 3 of the Online Appendix. To summarize, we regress premium on leverage at the fund level under different specifications of fixed effects (fund and time), all of which show a positive and statistically significant coefficient and a large $R$-squared ranging from 0.56 to 0.84. Overall, it is clear that most of the variation in the B premium was driven by the embedded leverage. Therefore, if leverage were to experience a sudden drop (e.g., a reset), one should rationally expect the premium to shrink immediately.

[13] Equity holding includes all exchange-traded equity products such as individual stocks and ETFs. We do not observe 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.

[14] 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.

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 arbitrageurs 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 substantially underpriced, as Figure 2 shows. 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."[15]

**Restructuring events.** Again, to ensure the low-risk feature of A funds, B funds had restructuring clauses to reset leverage when the NAV of the underlying assets dropped 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.[16] Many funds were forced to reset their leverage back to one, 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 market 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 this event study in Section 4.

## 2.4 Data

We use two main datasets, both from a large national brokerage in China. 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 of all exchange-traded products from 2006 to 2016. We focus on three types of assets: AB funds, ETFs, and individual stocks. The brokerage data include almost three million retail investors—around 5% of the entire investor population in China. Out of the three million investors, 1.2 million are considered "active"; that is, they both

[15] We include additional analysis of the limits to arbitrage in Section 4 of the Appendix.

[16] In Section 7 of the Online 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.

bought and sold at least 10 times during their transaction history. Table 4 shows 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 survey responses is in Section 2 of the Online Appendix. Surveys are voluntary when an investor opens her first brokerage account; 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 entry decisions into B funds, we use survey-based characteristics as control variables.

We construct several 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 can identify the small number of transactions made by institutional investors.

# 3 Wealth Consequences of B Funds

## 3.1 Overview of B returns

Figure 3 plots the cumulative RMB returns and return rates for all B investors from 2014 to 2016 and shows large profits accumulated during the market run-up from December 2014 to May 2015. When the market peaked in early June, investors were at a gain of a little over 2 billion RMB. Conditional on participation, this was almost 20,000 RMB per capita. These gains were completely wiped out during the market crash that started in mid-June. Due to leverage, B returns dropped sharply and, by the end of 2015, B investors as a whole had approximately broken even. The

market dropped further in early 2016 and remained relatively stable for the rest of the year. Given the muted market reactions in 2016, we will focus on 2014–2015 in subsequent discussion about B fund returns. Because aggregate returns overweigh wealthy investors, Table 5 instead shows the distribution of investor-level profits. Returns are calculated for three sub-periods: during the quiet, during the run-up, and during the crash.[17] 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 RMB in the crash.

To further examine B returns across investors by controlling for investment size, Panels B to D present summary statistics for return rates based on three methods: first, returns are based on maximum balance; second, on average balance; and third, on maximum investment.[18] That is, we take the sum of investor profits over the period and scale by one of the three measures. Unsurprisingly, average return rates are positive during the quiet and run-up periods and negative during the crash. Return rates positively skewed in the run-up, but negatively skewed in the crash. 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 roughly broke even from 2014 to 2015, we now examine the distribution of returns across investor groups. In particular, we focus on wealth, a proxy for sophistication and important consideration in studies of wealth inequality, but we also consider other proxies for sophistication.

[17]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 of 2014–2015 is the quiet period. See Liao et al. (2021) for a more detailed explanation about the timeline of the bubble.

[18]Calculating return rates at the investor level requires making assumptions about the amount of invested capital. We consider three measures. The first is maximum balance, which effectively measures the maximum B fund investment that existed in the account at the end of the day. The second is average B fund balance to date, where balance is calculated daily. The third is maximum investment, which measures the initial B fund balance at the beginning of each sub-period plus the maximum cumulative net flow into B funds during that sub-period. By definition, maximum balance is greater than or equal to average balance. In most cases, maximum balance is greater than maximum investment because of the market run-up in the first half of 2015.

### 3.2.1 Wealth

Earlier papers use wealth as a proxy for financial sophistication and find substantial heterogeneity in investment behavior and return (e.g., Calvet et al. 2007). 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, we compare those in the top 1% and those in the bottom 99%, with 5 million RMB as the cutoff point.[19] 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, by the end of 2015, the top 1% made a total profit of 500 million RMB, whereas the bottom 99% lost 500 million RMB, resulting in a difference in total profits of 1 billion RMB from the poor to the rich and a wealth transfer of 500 million RMB from the poor to the rich.[20] Similarly, Sub-figure 4b shows that, between 2014 and 2015, 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 350 million RMB. Because our data cover around 5% of the entire investor population, these numbers suggest a total wealth transfer of 7 to 10 billion RMB from the poor to the rich in just two years. These gaps persisted or widened throughout 2016.

The gap in returns primarily stems from the crash. In Sub-figure 4a, 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. Due to differences in initial investment, this pattern is less observable in Sub-figure 4b. Sub-figure 4d, however, shows a similar pattern in terms of return rates.

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

[20] 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.

The above result also connects to studies of the rising wealth inequality in the US and the rest of the world.[21] A striking finding 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 from the supply side.

### 3.2.2 Other measures of sophistication

We next examine other measures of sophistication. 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 was a wealth transfer of 200 million from the low-literacy group to the high-literacy group and of 250 million from the non-college-educated group to the college-educated group. Extrapolating these numbers to the entire population suggests a total wealth transfer of 4 to 5 billion RMB.

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 sophisticated investors did better during the crash is that they knew how to deal with the downside risk shrouded by complexity.

### 3.2.3 Regressions

To establish the observations from Figures 4 to 5 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 Section 5 of the Online 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

[21] See Benhabib and Bisin (2018) for a recent review.

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 naive to the sophisticated. However, given the mounting evidence that financial sophistication—measured by wealth, education, and IQ—matters for investment performance, it is not surprising to see a similar gap in the return of complex financial products (Calvet et al. 2007; Grinblatt et al. 2012; An et al. 2019). We argue, however, that investor heterogeneity in skills is not the sole force driving heterogeneous returns; more complex products from the supply side also contribute. As products become more complex, it allows the sophisticated investors to better take advantage of their superior skills—e.g., more timely information, better understanding of the product features and market microstructure, and greater awareness of risk management.

To test this hypothesis, we consider a product without the complex features: (simple) ETFs. Indeed, just as MBSs are derived from a pool of mortgages, structured funds are products 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. As a benchmark, Figure 6 plots the cumulative returns from trading ETFs for the *same* group of investors. Overall, they did much better trading ETFs, making a total profit of around 300 million RMB.

Figure 7 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 7a, small investors actually make more profits than large investors due to a greater initial investment. In Sub-figures 7b and 7c, the direction of the transfer is consistent with that for B funds, but the magnitude is much smaller. Figure 8 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 5.

Table 7 puts all the four variables considered so far in the same regression and additionally controls for gender and experience. 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. Compared to the average investor, those 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 returns as a control variable. Therefore, 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 7 shows, 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 8, 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 investment mistakes (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 more clearly 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 Section 6 of the Online Appendix. All the above patterns are robust in this slightly smaller set of funds.

# 4 Event Study: Restructuring Events

The comparison between B funds and ETFs in Section 3 showed how adding complexity to simple securities can lead to greater cross-subsidization from the naive to the sophisticated. In this section, we provide evidence that directly ties the complexity of B funds to this cross-subsidization. In particular, we zoom into the 2015 Chinese 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 when knowledge about the complex features mattered the most.

## 4.1 Overview of restructuring events

When the per-share NAV of a B fund drops below the pre-specified threshold (typically, and assumed henceforth to be, 0.25 RMB), restructuring begins and usually takes two days to complete. Day 0, known as the "event day," is when the NAV falls below 0.25 RMB for the first time. On day 1, trading continues. However, even if the 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 is suspended and leverage is reset according to the NAV at close on day 1. Trading resumes on day 3.

Consider Penghua One-Belt-One-Road B Fund for a more concrete example. In Sub-figure 9a its per-share NAV dropped from 0.81 to 0.29 between June 24 and July 7, 2015. At the same time, the premium rose from 23% to almost 74%. On July 8, the NAV closed at 0.24, crossing the 0.25 threshold for the first time and triggering the restructuring event. Per the restructuring rules, trading would continue as usual on July 9 and the restructuring was scheduled for July 10 (Friday). Indeed, as Sub-figure 9b shows, trading was intensive on July 9. After restructuring, trading resumed on July 13 (Monday) with the leverage ratio reset to 1:1. The premium, however, disappeared, and Penghua B shares halved in market capitalization from the previous trading day.

Similar episodes abounded during the crash. In Figure 10, Sub-figure 10a 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 almost completely disappeared.

## 4.2 Ex-ante knowledge

While it was clear ex-post that leverage resets would eliminate the B premium, it was less obvious that rational investors could predict this ex-ante. We believe they should have been able to make this prediction for multiple reasons. As discussed in Section 2.3.2, if investors knew about the relationship between leverage and premium, then they should rationally expect the large premium to shrink after leverage reset. Since both price and NAV were directly observable to investors, it was straightforward for them to calculate premium and leverage and infer their relationship. They also should have been able to anticipate a leverage reduction from restructuring since (i) restructuring clauses were clearly stated in prospectuses and (ii) investors received reminder notifications from their brokers when the NAV approached the threshold. Therefore, investors had the necessary information to make the correct inference about post-restructuring premium.

Relatedly, investors could rationally expect a reduction in premium by examining premiums of funds with a leverage ratio close to one. We examine all instances in which a fund was trading at a leverage ratio close to one prior to the crash.[22] Both the medium and average were about 7%, consistent with a positive B premium on average. However, this was an order-of-magnitude smaller than the average 100% premium prior to restructuring. In fact, the maximum premium was around 50%, which still would imply a sizable drop in premium after leverage reset.

Additionally, while leverage drives most of the premium, part of it—especially on days $-1$ and 0—was also induced by the daily price limit rule imposed by the regulator, the China Securities Regulatory Commission (Chen et al. 2019). 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. Because this rule holds for both B funds and their underlying assets, it can mechanically create a premium due to leverage. For example, if the underlying assets drop by 8%, then a B fund with a leverage ratio of 2:1 should drop 16%. However, due to the negative 10% price limit, the B fund price can only drop 10%, which leads to an approximately

[22]The overall distribution of the B premium is included in Section 8 of the Online Appendix.

7% premium. After the leverage reset, trading would resume at the price of the new NAV, thereby directly eliminating the part of the premium induced by the rule. Given the ample liquidity available around the event day, as shown in Sub-figure 10b, investors could have easily sold their B shares prior to structuring to avoid such rule-induced losses.

For these reasons, we believe that the rational path of actions was well defined when restructuring events began to occur. As the NAV approached the restructuring threshold, the probability of restructuring increased dramatically. Knowing that restructuring means the disappearance of the premium, a rational investor should start selling her existing positions in B funds to avoid the downside risk. Even if, for some reason, she was left with a positive balance in B by the event day, she still had a chance to get out: she should try to sell as much as possible on day 1 when trading continues; she absolutely should not buy more.

## 4.3 Trading behavior around restructuring

How did investors actually respond to restructuring events? Sub-figure 11a plots the cumulative trading flow during the 21-day window around the event day. Retail investors, as a group, made very poor trades. 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. This behavior, given our discussion in the previous section, clearly suggests lack of rationality and a poor understanding of B funds' complex features.

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 10b 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 documented in Sub-figure 11a are conditional on the eventual realization of a restructuring event. While buying on day 1 is clearly a mistake, it remains possible to justify buying on day $-10$ to day 0. We present two pieces of evidence that casts doubt on this possibility.

First, it is possible B funds can rebound even after approaching the threshold, which could potentially offset the losses from restructuring events. 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 in asset value can make B's NAV cross the restructuring threshold. We find, in fact, that few funds, after approaching the threshold, resurrected. To show this, Sub-figure 11b plots the post-event retail flows and returns, where the event is defined by the first time a fund drops below 0.35.[23] Consistent with the above discussion, the post-event returns were largely negative.

Second, it is possible that we are observing the data from bad states of the world that were difficult to know ex-ante. To address this concern, we take the market return and volatility from historical data and calculate the expected return from investing in B funds for a risk-neutral investor; details are included in Section 9 of the Online Appendix. As B funds approach the threshold, the heightened risk of restructuring substantially bias the expected return downwards: on day 0, the expected return from investing in B funds is more than $-20\%$ for the next month. Even before day 0, the expected return is largely negative on days $-2$ and $-1$. To summarize, even without risk aversion, investors need to have expectations that are significantly more optimistic than expectations based on historical patterns to justify their behavior.

## 4.4 Heterogeneity

Subsection 4.3 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 investors handle restructuring events better?

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

Figure 12 shows the cumulative trading flows during the 21-day window around the event day for investor groups sorted on measures of sophistication. In Sub-figure 12a, B funds had a net outflow of around 10% from the top 1% investors in the 11-day window prior to the event day. This suggests that they gradually took money out—albeit only partially—in anticipation of restructuring. During the same window, the bottom 99% investors had a net inflow of almost 20%, suggesting unawareness of the substantial downside. The difference in cumulative return rates between the two groups reached almost 12% on the event day and further rose to 18% post restructuring. The widening of the return rate difference post-restructuring is a result of the premium elimination. Differences in returns and trading flows remained rather stable afterwards. Sub-figures 12b to 12d show similar patterns, 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, and their gap in cumulative return rates reached 10% post restructuring. Overall, sophisticated investors handled restructuring events better than naive investors.

How much of the wealth transfers documented in Figure 4 can be attributed to these restructuring events? 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 total transfer shown in Figure 4a, we can attribute 25% to the restructuring day and 45% to the 21-day window.

## 4.5 Evidence of learning

We argued above that the differences in trading behavior around restructuring events were driven by differences in understanding about B funds. In this subsection, we present two additional pieces of evidence in support of this mechanism.

First, if ignorance about restructuring events underlies trading behavior before restructuring, then we should expect this pattern to decay over time as news of investors suffered losses gets publicized and more people learn about restructuring clauses. We examine the changes in trading behavior across three waves of restructuring events: first in early July, second in late August, and third in early 2016.[24] Figure 13a documents how trading behavior around restructuring events

[24]Because restructuring events are more likely to happen when the market plummets, they typically come in waves.

differs across the three waves. Consistent with learning, retail investors increased their positions less and lost less money in later events.

Second, we further examine the latter two waves to compare investors with and without prior trading experience B funds. Figure 13b shows that the reduction in buying prior to restructuring is more pronounced among investors who held B funds right through prior restructuring events, suffered losses when the premium disappeared, and were more likely to have obtained knowledge about the return implications of restructuring events. This evidence further supports the notion that, as time passes, investors learn more about complex products, which helps improve their financial outcomes.

## 4.6 Other explanations for investor heterogeneity

### 4.6.1 Heterogeneous risk preferences

One explanation that can rationalize the differences in trading behavior is heterogeneous risk preferences. We argue that this is unlikely to explain our results. Standard theories of risk preference suggest risk aversion decreases with wealth. This would imply that, as downside risk heightened when B funds approached the threshold, the rich should be the ones holding the B shares.

Theories based on non-standard preferences can also be evoked to explain the different trading patterns. One candidate is gambling preference: naive investors are more prone to gambling and betting more on an eventual resurrection. Three pieces of evidence cast doubt on this explanation. First, given that risk preference is relatively persistent at the individual level (e.g., Dohmen et al. 2011), we should expect to see similar reactions across time. The fact that the patterns decay over time suggests that it is not innate preference driving behavior. Second, as discussed above, while gambling preference in theory could explain increased holdings prior to restructuring, it cannot explain why some investors increased their holdings on day 1. Third, below in Section 4.7 we show that while, indeed, gambling preference may be driving some investors' behavior, the overall explanatory power is small. For the majority of investors, their behavior appears uncorrelated to gambling preference.

#### 4.6.2 Heterogenous beliefs

Another possible explanation rests on heterogeneous and incorrect beliefs about restructuring events. For example, if sophisticated investors are more extrapolative, then they are more likely to get out before structuring events as B shares keep dropping in value. This alternative explanation faces similar challenges as above: it cannot explain the learning over time in Section 4.5 and the buying on day 1. It also contradicts the common interpretation that extrapolation represents naivety (Greenwood and Shleifer 2014; Da et al. 2021). Furthermore, extrapolation has little explanatory power for trading behavior around structuring events, although it explains the initial entry decisions very well.[25]

#### 4.6.3 Liquidity provision

In a related study, Li et al. (2020) find that large investors act as liquidity providers in the Chinese warrants market. 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 de-facto 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.

#### 4.6.4 Liquidity shock

It is also possible that large investors, during the market crash, 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

[25] Results are omitted for brevity and available upon request.

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.

#### 4.6.5 Reluctance to realize losses

The better performance of large investors, especially during the crash, could involve the mechanisms of the disposition effect (Odean 1998); that is, the propensity to realize gains and avoid losses. Because sophisticated investors display a weaker disposition effect (Dhar and Zhu 2006), 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.

#### 4.6.6 Inattention

Another explanation 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 11a.

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.

## 4.7 Why did small investors increase their positions?

Our discussion above suggests that competing explanations based on heterogeneous preferences and beliefs, liquidity provision, liquidity shocks, behavioral biases such as the disposition effect, and inattention cannot account for the observed differences of responses between sophisticated investors and naive investors. We therefore conclude that the most likely explanation is that the sophisticated understood these products better and were better able to navigate the risks from restructuring events.

However, a lack of understanding of complex products does not explain why the naive *increase* their holdings rather than do nothing. In this subsection, 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 can be associated with greater demand for leverage.

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.[26] 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 account balance. 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 constrained investors, using each identification method, increased their holdings more than unconstrained investors prior to restructuring.

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

## 4.8 Other discussions

### 4.8.1 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.[27] 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.

### 4.8.2 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 also 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 structuring 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 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

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

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. 2021), demand for leverage (Bian et al. 2021), 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 Online 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 growing evidence of their dangers. This evidence shows that issuers can use complexity to enrich their coffers by tricking unsophisticated investors into buying products at inflated prices. We show that the dangers of complex products to the unsophisticated extend beyond issuance. Specifically, we show that, even in a setting devoid of brokers' perverse incentives, 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.

# References


Allen, F., Gale, D., et al. (1994). *Financial innovation and risk sharing*. MIT Press, Cambridge MA.

An, L., Bian, J., Lou, D., and Shi, D. (2019). Wealth redistribution in bubbles and crashes. *Working paper*.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2015). X-CAPM: An extrapolative capital asset pricing model. *Journal of Financial Economics*, 115(1):1–24.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, 129:203–227.

Benhabib, J. and Bisin, A. (2018). Skewed wealth distributions: Theory and empirics. *Journal of Economic Literature*, 56(4):1261–1291.

Bhattacharya, V., Illanes, G., and Padi, M. (2020). Fiduciary duty and the market for financial advice. *Working paper*.

Bian, J., Da, Z., He, Z., Lou, D., Shue, K., and Zhou, H. (2021). Margin trading and leverage management. *Working paper*.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2016). Competition for attention. *Review of Economic Studies*, 83(2):481–513.

Calvet, L. E., Campbell, J. Y., and Sodini, P. (2007). Down or out: Assessing the welfare costs of household investment mistakes. *Journal of Political Economy*, 115(5):707–747.

Calvet, L. E., Célérier, C., Sodini, P., and Vallee, B. (2020). Can security design foster household risk-taking? *Working paper*.

Campbell, J. Y. (2006). Household finance. *Journal of Finance*, 61(4):1553–1604.

Campbell, J. Y. (2016). Restoring rational choice: The challenge of consumer financial regulation. *American Economic Review*, 106(5):1–30.

Campbell, J. Y., Ramadorai, T., and Ranish, B. (2019). Do the rich get richer in the stock market? Evidence from India. *American Economic Review: Insights*, 1(2):225–240.

Carlin, B. I., Kogan, S., and Lowery, R. (2013). Trading complex assets. *Journal of Finance*, 68(5):1937–1960.

Célérier, C. and Vallée, B. (2017). Catering to investors through security design: Headline rate and complexity. *Quarterly Journal of Economics*, 132(3):1469–1508.

Chang, E. C., Tang, D. Y., and Zhang, M. B. (2015). Suitability checks and household investments in structured products. *Journal of Financial and Quantitative Analysis*, 50(3):597–622.

Chen, T., Gao, Z., He, J., Jiang, W., and Xiong, W. (2019). Daily price limits and destructive market behavior. *Journal of Econometrics*, 208(1):249–264.

Da, Z., Huang, X., and Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1):175–196.

Dhar, R. and Zhu, N. (2006). Up close and personal: Investor sophistication and the disposition effect. *Management Science*, 52(5):726–740.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3):522–550.

Duffie, D. and Rahi, R. (1995). Financial market innovation and security design: An introduction. *Journal of Economic Theory*, 65(1):1–42.

Egan, M. (2019). Brokers versus retail investors: Conflicting interests and dominated products. *Journal of Finance*, 74(3):1217–1260.

Egan, M., Matvos, G., and Seru, A. (2019). The market for financial advisor misconduct. *Journal of Political Economy*, 127(1):233–295.

Ellison, G. (2005). A model of add-on pricing. *Quarterly Journal of Economics*, 120(2):585–637.

Fagereng, A., Guiso, L., Malacrino, D., and Pistaferri, L. (2020). Heterogeneity and persistence in returns to wealth. *Econometrica*, 88(1):115–170.

Gabaix, X. (2019). Behavioral inattention. In *Handbook of Behavioral Economics: Applications and Foundations 1*, volume 2, pages 261–343. Elsevier.

Gabaix, X. and Laibson, D. (2006). Shrouded attributes, consumer myopia, and information suppression in competitive markets. *Quarterly Journal of Economics*, 121(2):505–540.

Ghent, A. C., Torous, W. N., and Valkanov, R. I. (2017). Complexity in structured finance. *Review of Economic Studies*, 86(2):694–722.

Greenwood, R. and Shleifer, A. (2014). Expectations of returns and expected returns. *Review of Financial Studies*, 27(3):714–746.

Grinblatt, M., Keloharju, M., and Linnainmaa, J. T. (2012). IQ, trading behavior, and performance. *Journal of Financial Economics*, 104(2):339–362.

Heimer, R. and Imas, A. (2020). Biased by choice: How access to leverage exacerbates financial mistakes. *Working paper*.

Heimer, R. and Simsek, A. (2019). Should retail investors' leverage be limited? *Journal of Financial Economics*, 132(3):1–21.

Henderson, B. J. and Pearson, N. D. (2011). The dark side of financial innovation: A case study of the pricing of a retail financial product. *Journal of Financial Economics*, 100(2):227–247.

Jarrow, R. A. and O'Hara, M. (1989). Primes and scores: An essay on market imperfections. *Journal of Finance*, 44(5):1263–1287.

Kumar, A. (2009). Who gambles in the stock market? *Journal of Finance*, 64(4):1889–1933.

Li, X., Subrahmanyam, A., and Yang, X. (2020). Winners, losers, and regulators in a derivatives market bubble: Evidence from Chinese brokerage data. *Review of Financial Studies, Forthcoming*.

Liao, J., Peng, C., and Zhu, N. (2021). Extrapolative bubbles and trading volume. *Working paper*.

Lusardi, A. and Mitchell, O. S. (2014). The economic importance of financial literacy: Theory and evidence. *Journal of Economic Literature*, 52(1):5–44.

Odean, T. (1998). Are investors reluctant to realize their losses? *Journal of Finance*, 53(5):1775–1798.

Olafsson, A. and Pagel, M. (2017). The ostrich in us: Selective attention to financial accounts, income, spending, and liquidity. *Working paper*.

Pearson, N., Yang, Z., and Zhang, Q. (2020). The Chinese warrants bubble: Evidence from brokerage account records. *Review of Financial Studies, Forthcoming*.

SEC (2011). Staff summary report on issues identified in examinations of certain structured securities products sold to retail investors.

Seru, A., Shumway, T., and Stoffman, N. (2010). Learning by trading. *Review of Financial Studies*, 23(2):705–739.

Shin, D. (2019). Extrapolation and complexity. *Working paper*.

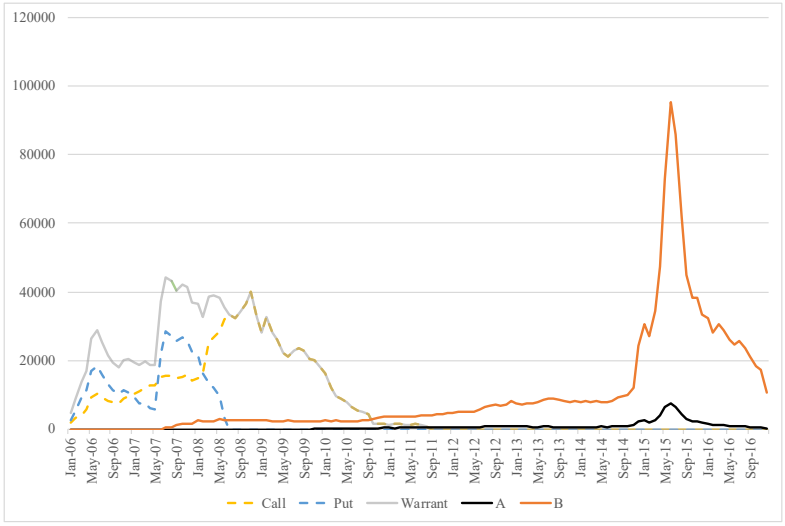
Shleifer, A. and Vishny, R. W. (1997). The limits of arbitrage. *Journal of Finance*, 52(1):35–55.

Sicherman, N., Loewenstein, G., Seppi, D. J., and Utkus, S. P. (2016). Financial attention. *Review of Financial Studies*, 29(4):863–897.

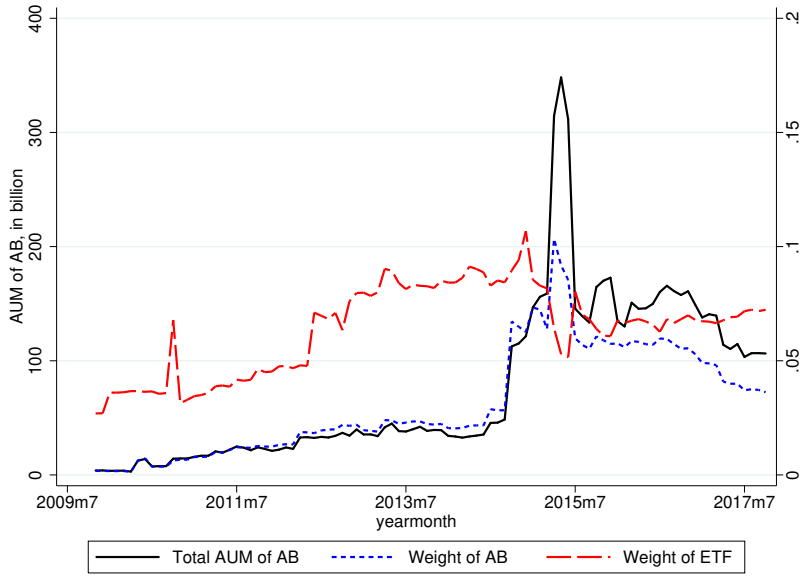
Van Rooij, M., Lusardi, A., and Alessie, R. (2011). Financial literacy and stock market participation. *Journal of Financial Economics*, 101(2):449–472.

Vokata, P. (2020). Engineering lemons. *Working paper*.

Xiong, W. and Yu, J. (2011). The Chinese warrants bubble. *American Economic Review*, 101(6):2723–2753.




(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.

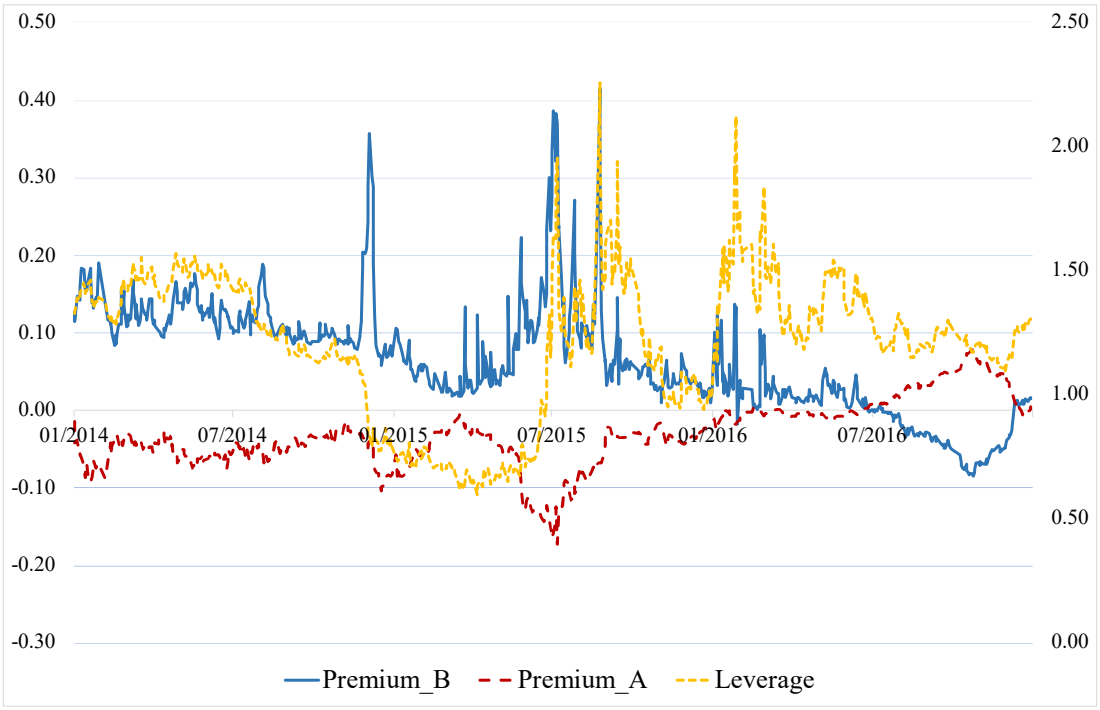



Figure 2: Time-series Variations of Leverage and Premium, 2014–2016

Note: Dynamics of the leverage and premium of AB funds between 2014 and 2016. 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.

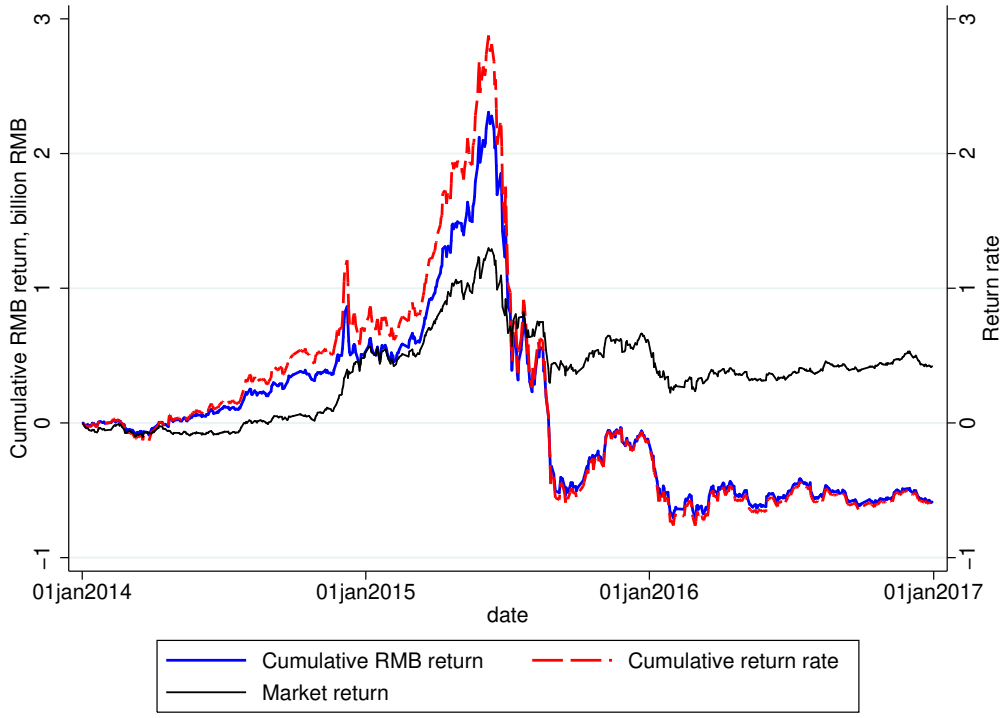
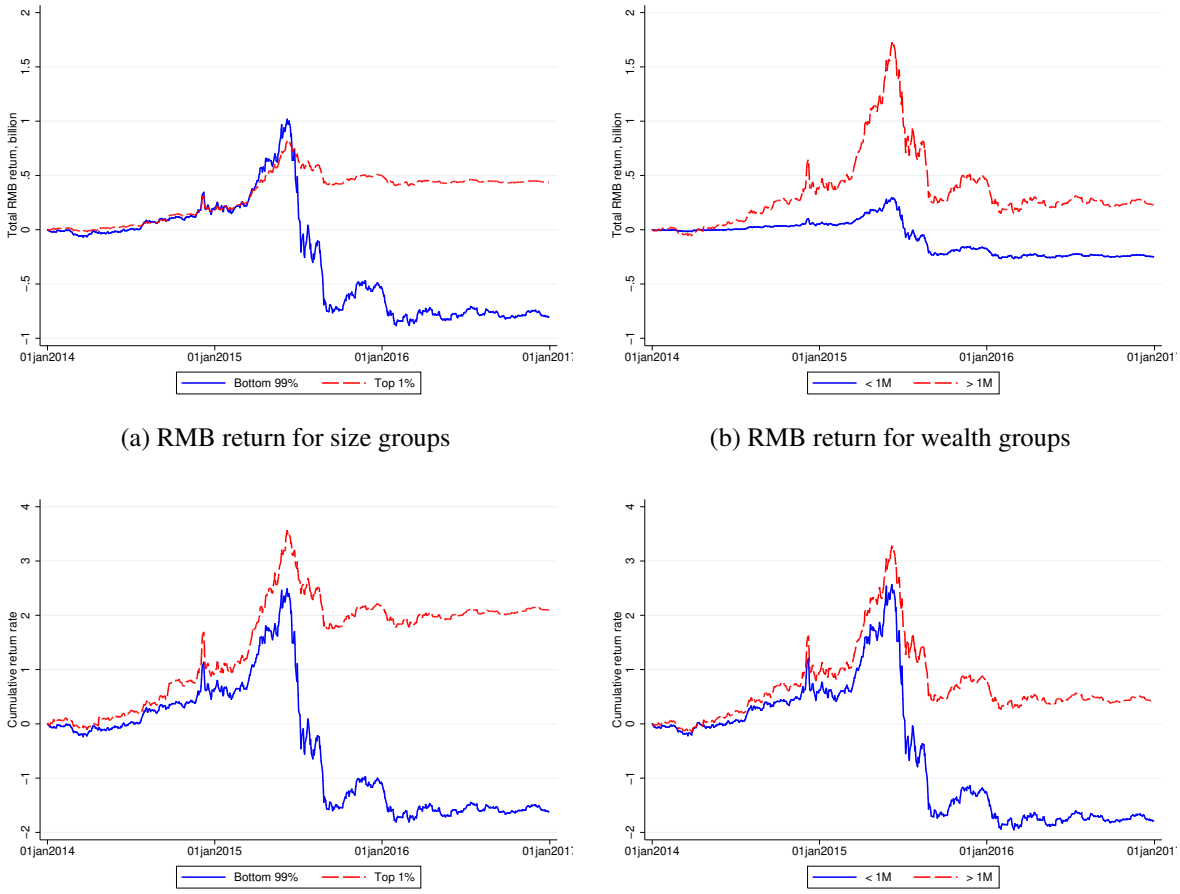



Figure 3: Cumulative Returns and Trading Flows of B Funds, 2014–2016

Note: Cumulative returns and flows from B funds from 2014 to 2016. 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 dividing cumulative RMB return by average investment calculated based on daily investment. The black solid line represents the market return.




(a) RMB return for size groups

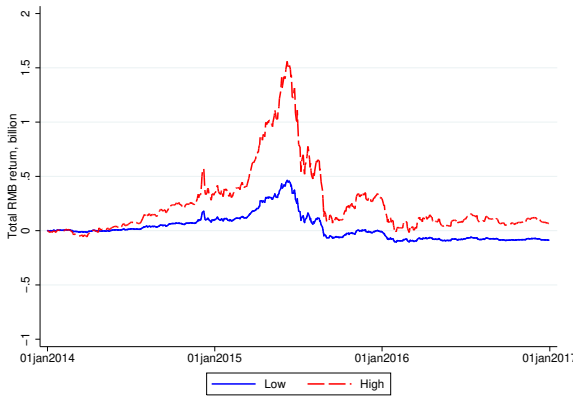
(b) RMB return for wealth groups

(c) Return rates for size groups

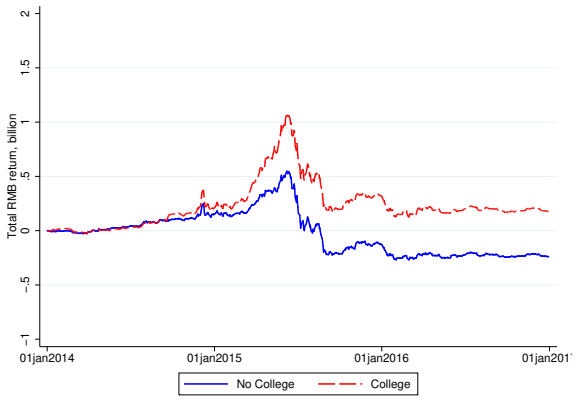
(d) Return rates for wealth groups

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

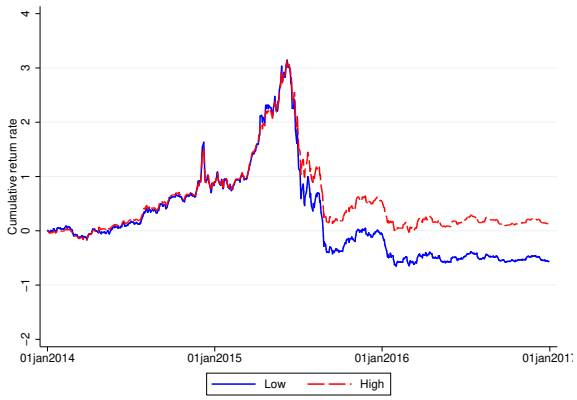
Note: Cumulative returns from B funds from 2014 to 2016 for investors of different wealth levels. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have a maximum account balance lower than 5 million RMB by the end of 2013. Wealth is based on self-reported wealth level. Return rates are calculated by dividing total RMB return by average daily balance.



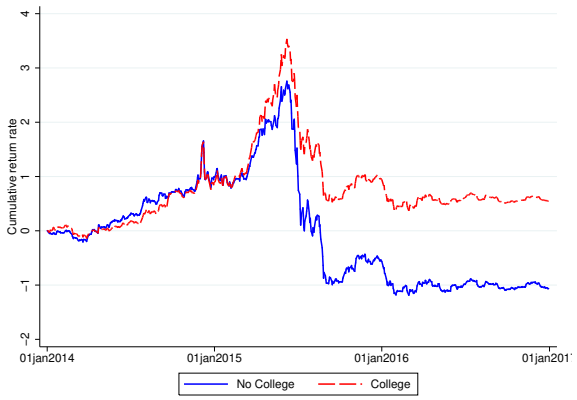

(a) RMB return for literacy groups




(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 2016 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.

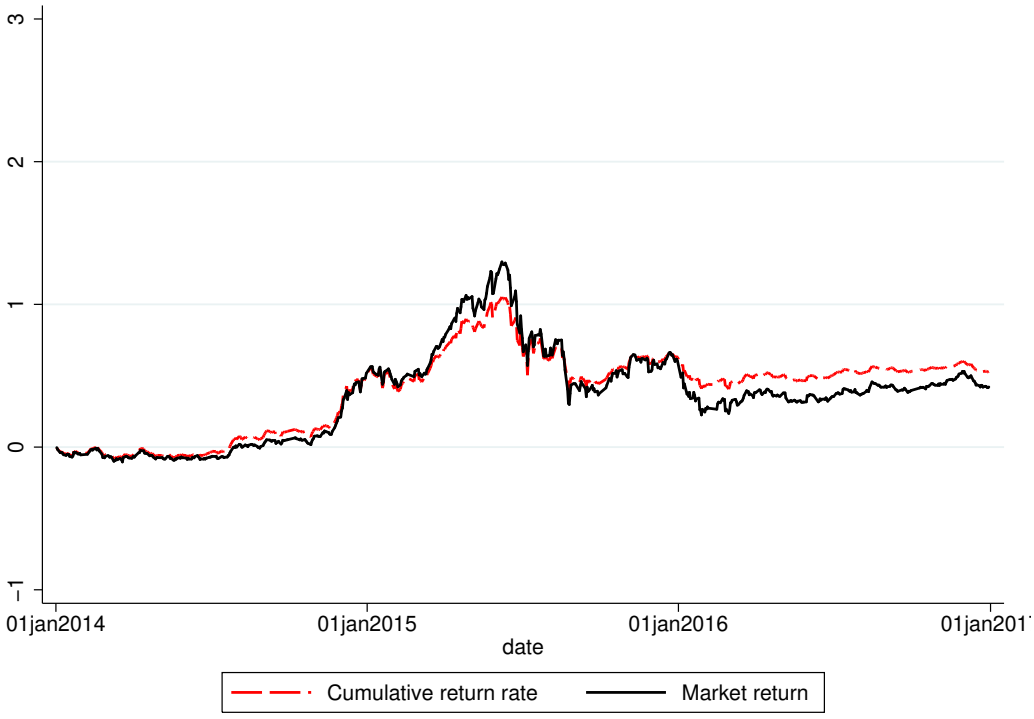
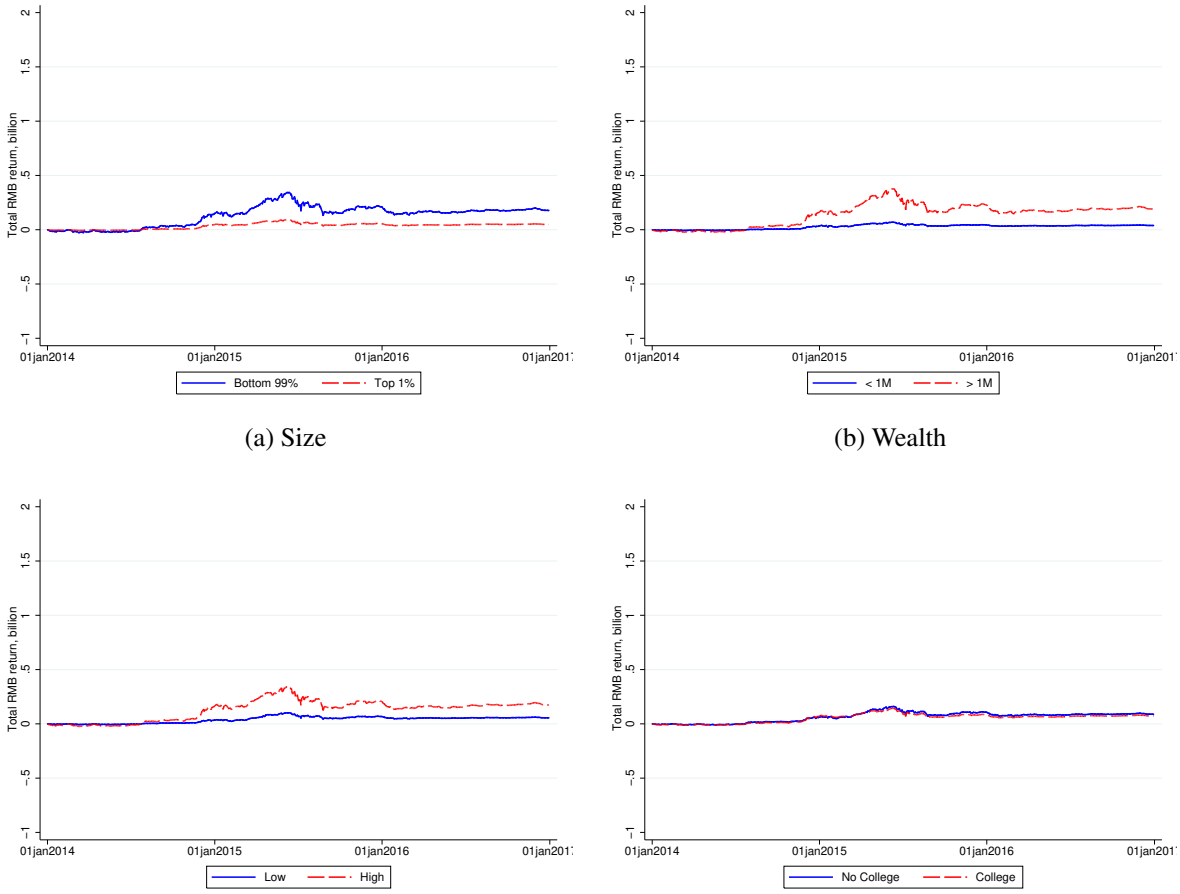



Figure 6: Cumulative Returns from ETFs, 2014-2016

Note: This figure plots cumulative returns and flows from ETFs from 2014 to 2016. The red dashed line represents cumulative return rate, calculated by dividing cumulative RMB return by average investment. The black solid line represents the market return.




(a) Size

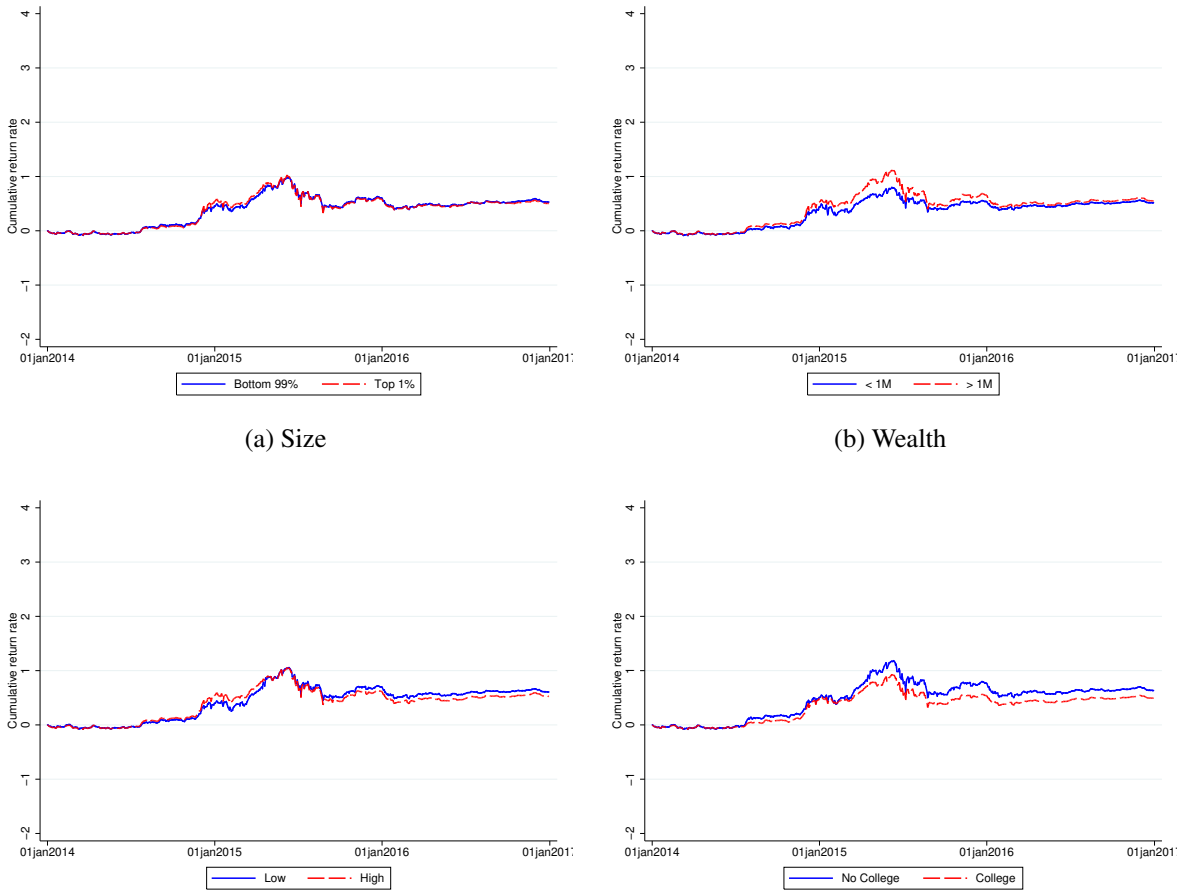
(b) Wealth

(c) Literacy

(d) Education

Figure 7: ETF RMB Returns for Investor Groups

Note: Cumulative returns from ETFs from 2014 to 2016 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

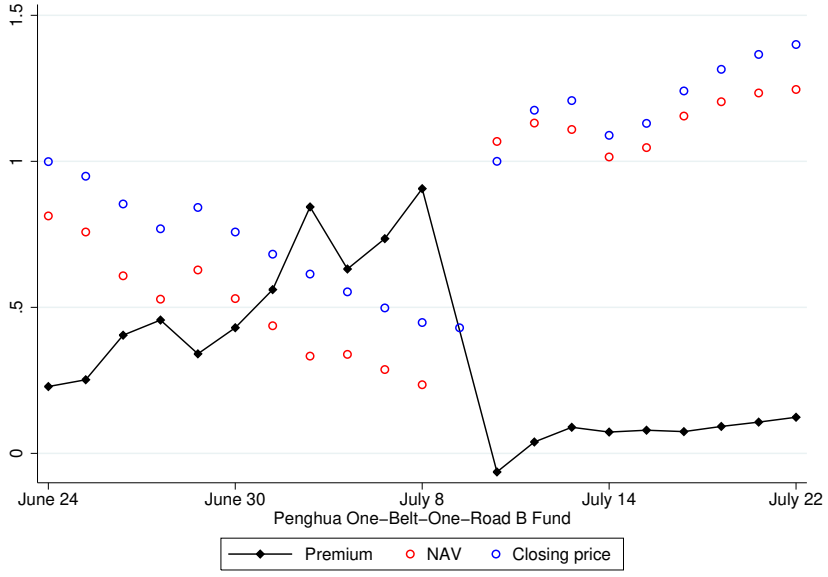
(b) Wealth

(c) Literacy

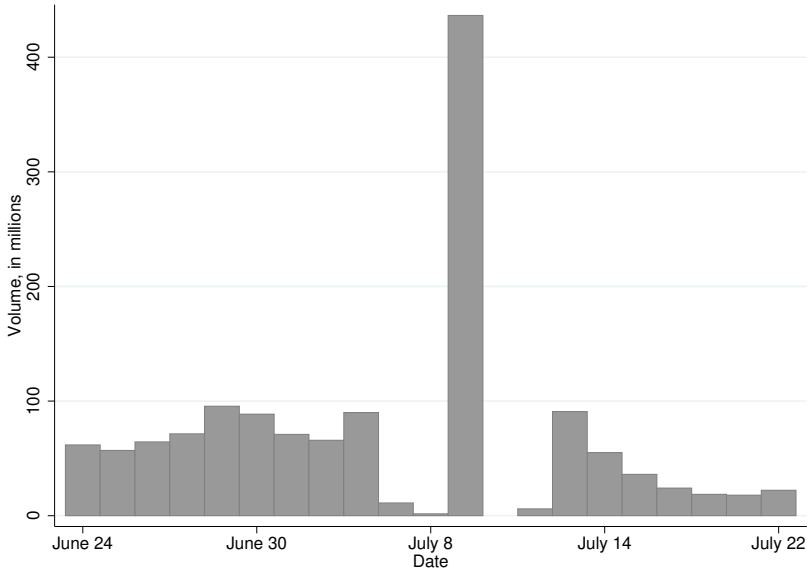
(d) Education

Figure 8: ETF Return Rates for Investor Groups

Note: Cumulative return rates from ETFs from 2014 to 2016 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.



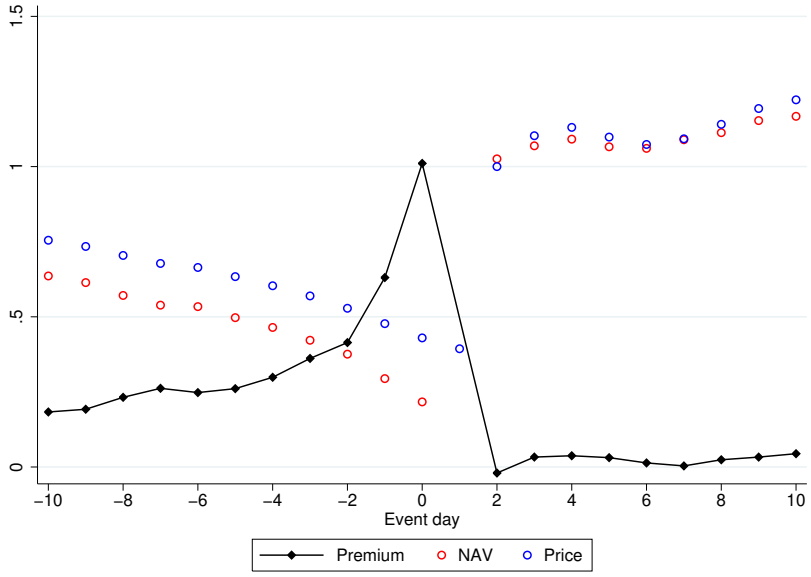

(a) Price and NAV



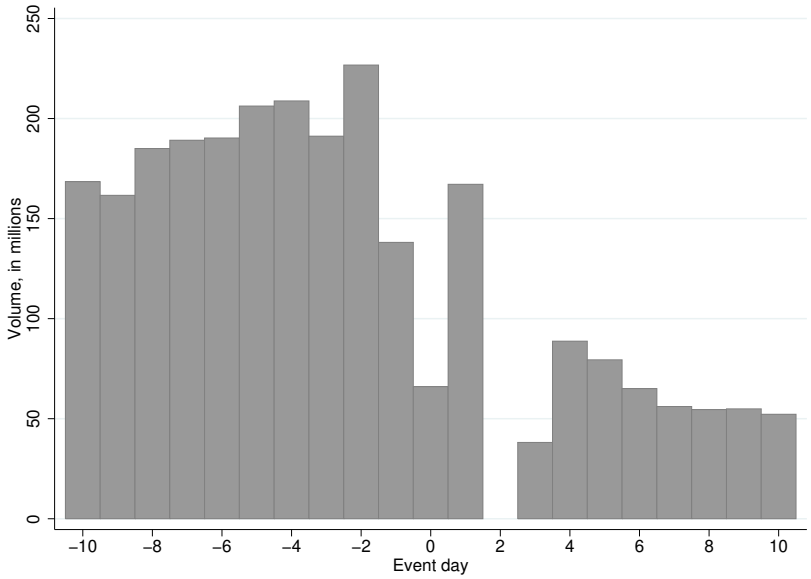

(b) Daily volume

Figure 9: Restructuring Event of Penghua B Fund

Note: Sub-figure 10 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 9b plots the daily trading volume during the same period.



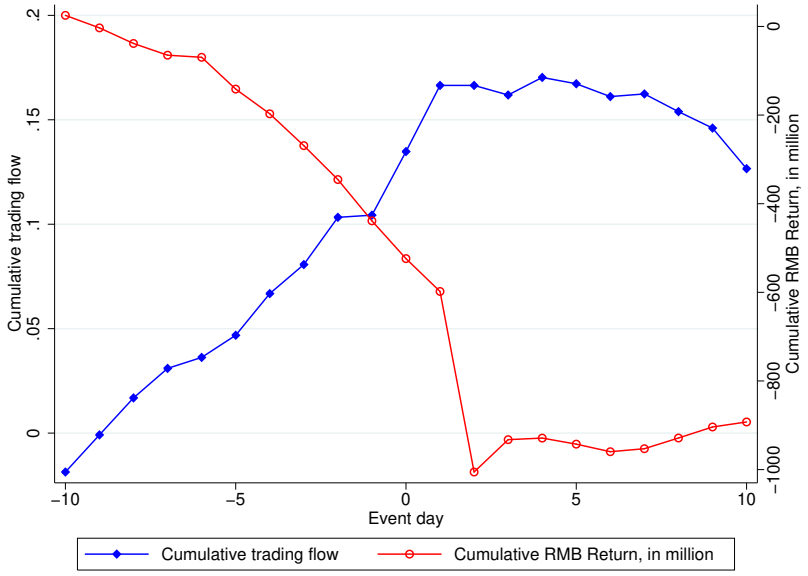

(a) All restructuring events



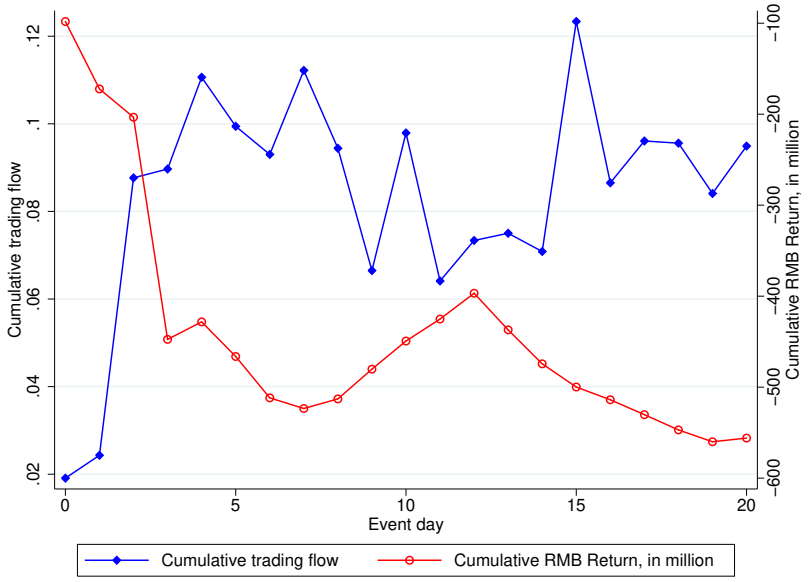

(b) Daily trading volume

Figure 10: B Funds during Restructuring Events

Note: Sub-figure 10a plots the evolution of NAV and price during the 21-day window around the restructuring events. Sub-figure 10b plots the daily trading volume averaged across all restructuring events. Day 0 is defined as the first time that a fund's closing price drops below the threshold.



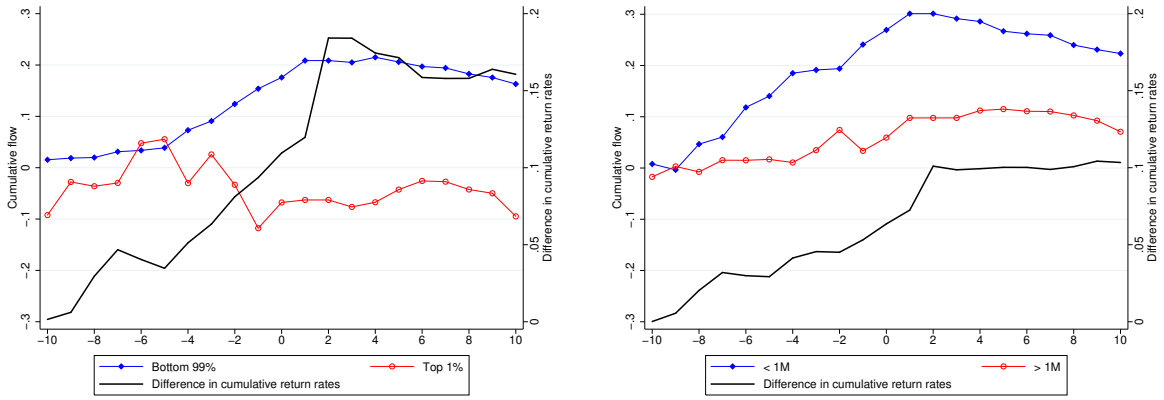

(a) All restructuring events (NAV $< 0.25$)




(b) NAV $< 0.35$

Figure 11: B Funds during Restructuring Events

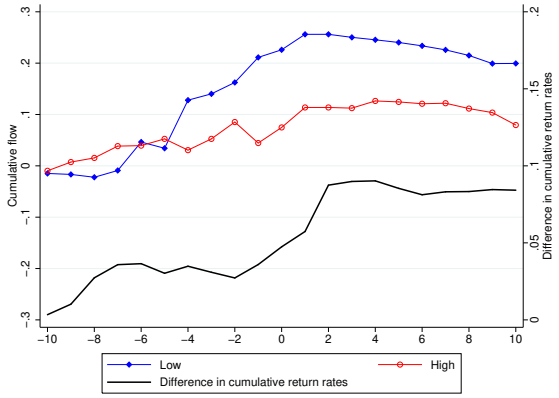
Note: Sub-figure 11a plots the distribution of trading flows around the restructuring events. Trading flow is normalized using the initial account balance. Sub-figure 11b plots the post-event trading flows and returns, where the event is defined by the first time a fund drops below 0.35.



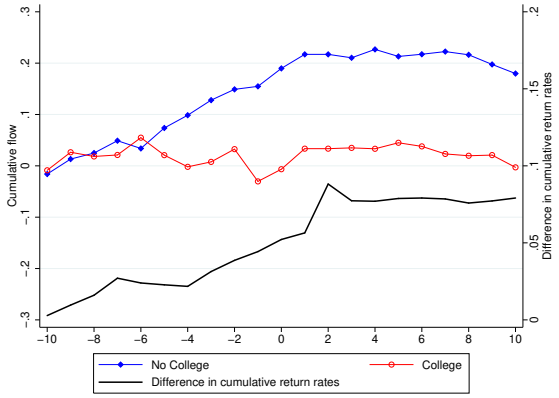

(a) Size




(b) Wealth



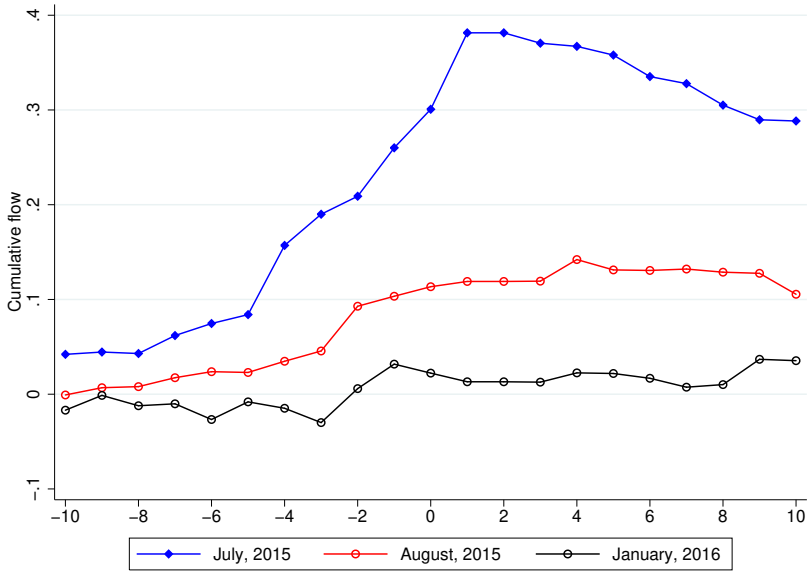

(c) Literacy



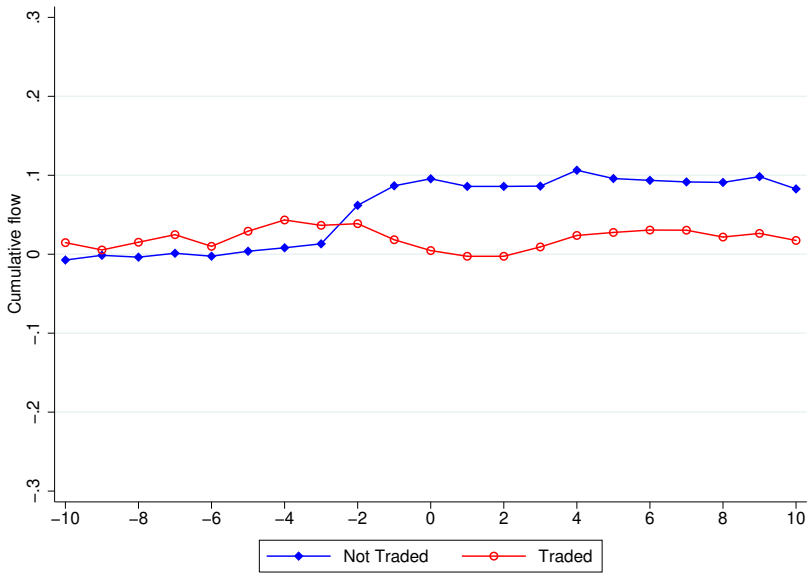

(d) Education

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.



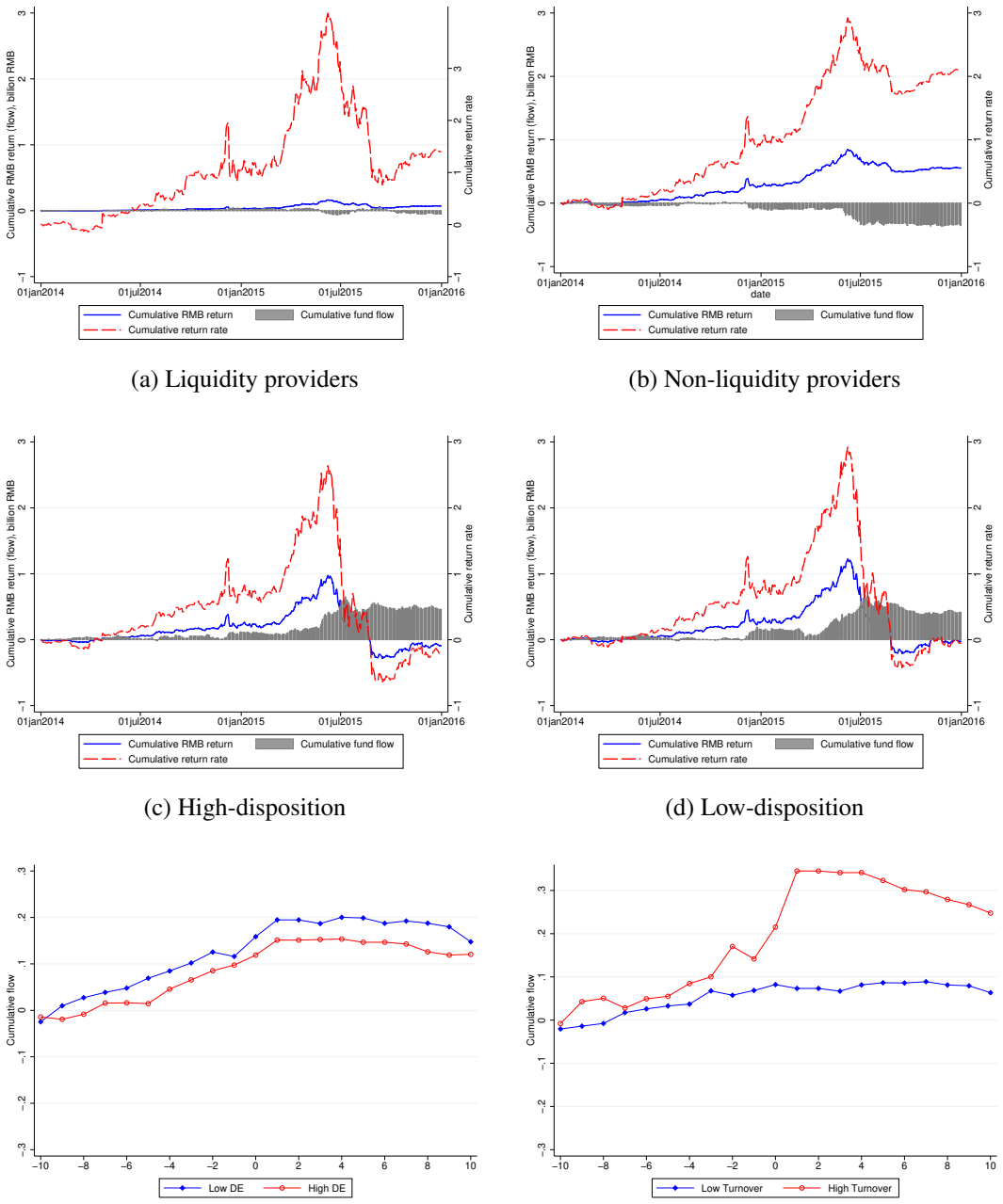

(a) Cumulative trading flow across waves




(b) Comparison between new and old investors

Figure 13: Evidence of Learning

Note: Figure 13a plots the cumulative trading flow around restructuring events for three different waves: first in early July, second in late August, and third in early 2016. Trading flow is normalized using the initial account balance. Figure 13b compares the cumulative trading flow, during the latter two waves, between investors with and without prior exposure to B funds' restructuring events, where prior exposure is defined by holding B funds throughout restructuring events.




(a) Liquidity providers

(b) Non-liquidity providers

(c) High-disposition

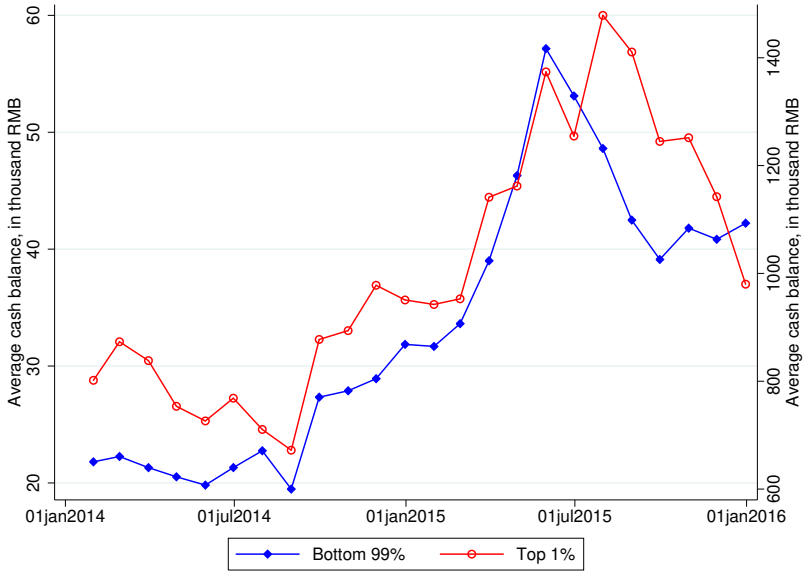
(d) Low-disposition

(e) Disposition effect

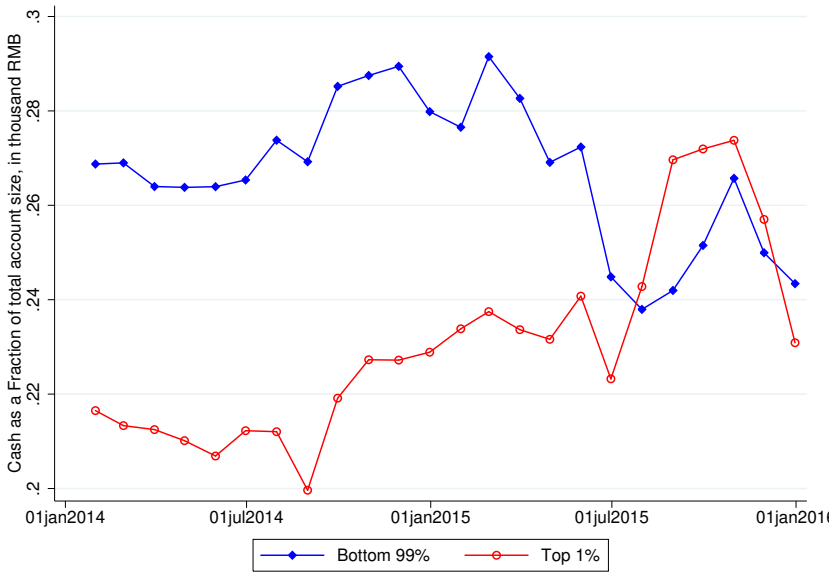
(f) Turnover

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.



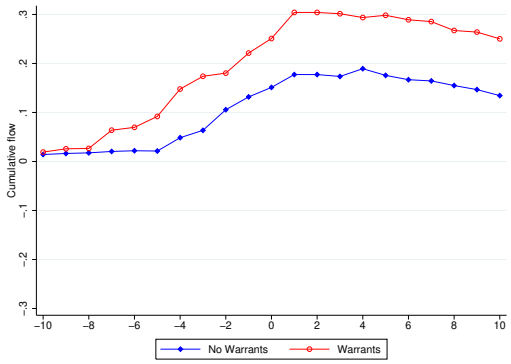

(a) Cash



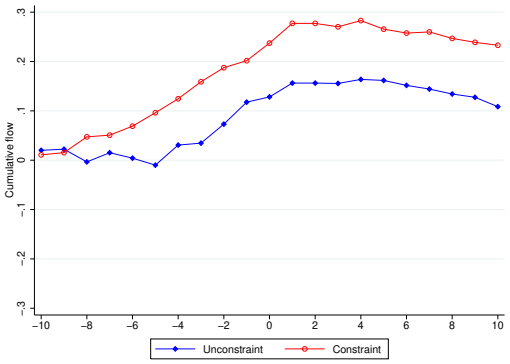

(b) Fraction of cash

Figure 15: Cash Holdings, 2014-2015

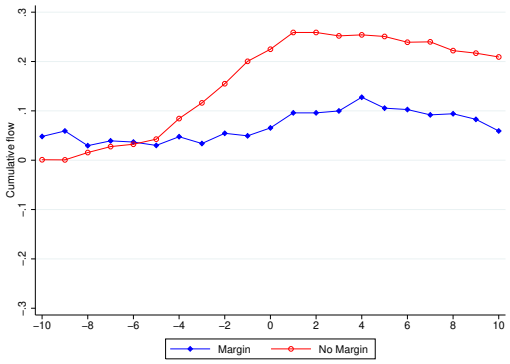
Note: Evolution of cash holdings for different investor groups. In Figure 15a, the left axis represents the bottom-99% investors and the right axis represents the top-1% investors. Cash represents the amount of cash balance in the account. Fraction of cash is calculated by dividing the amount of cash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




(a) Traded warrants before



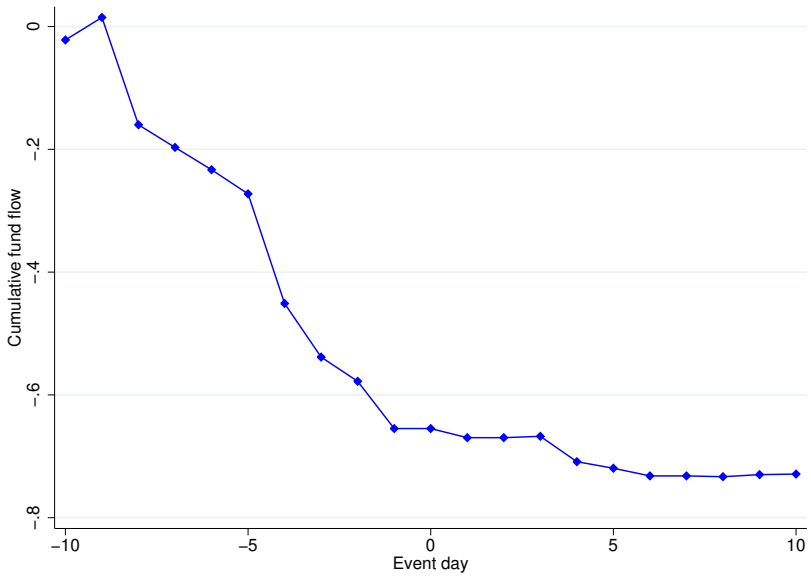

(b) Cash positions



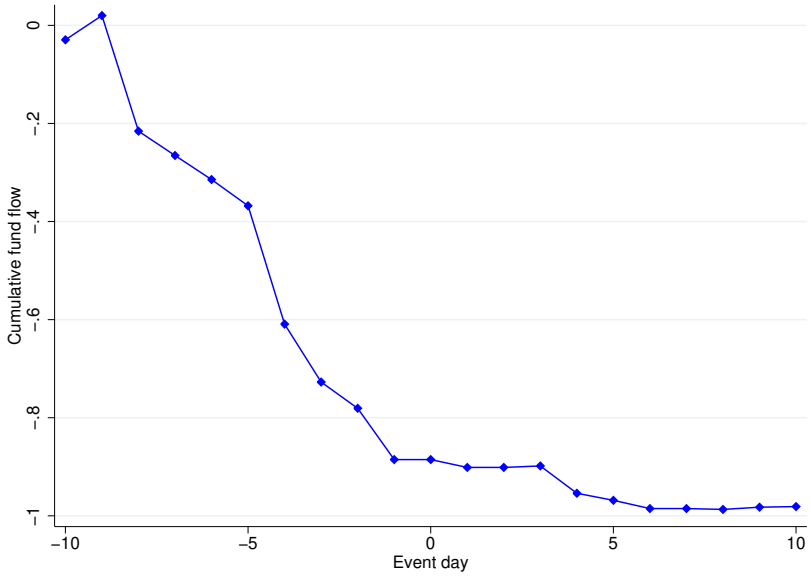

(c) Margin accounts

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 |
|---|---|---|---|---|
| Wealth (>1M) | 0.005*** | 0.023*** | | |
| | (0.001) | (0.003) | | |
| Size (top 1%) | | | 0.021*** | 0.038*** |
| | | | (0.005) | (0.013) |
| Constant | 0.057*** | -0.365*** | 0.062*** | -0.367*** |
| | (0.001) | (0.002) | (0.001) | (0.002) |
| Observations | 47,814 | 40,655 | 51,176 | 45,892 |
| *R*-squared | 0.000 | 0.001 | 0.000 | 0.000 |

| | Run-up | Crash | Run-up | Crash |
|---|---|---|---|---|
| Financial literacy (good) | 0.009*** | 0.025*** | | |
| | (0.001) | (0.003) | | |
| College | | | 0.003** | 0.008** |
| | | | (0.002) | (0.004) |
| Constant | 0.054*** | -0.368*** | 0.057*** | -0.363*** |
| | (0.001) | (0.003) | (0.001) | (0.002) |
| Observations | 47,814 | 40,655 | 37,339 | 33,050 |
| *R*-squared | 0.001 | 0.001 | 0.000 | 0.000 |

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.

| | 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 Online Appendix. Standard errors are clustered at the investor and month levels.

# Online Appendix for

# “Exploited by Complexity”

# 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.

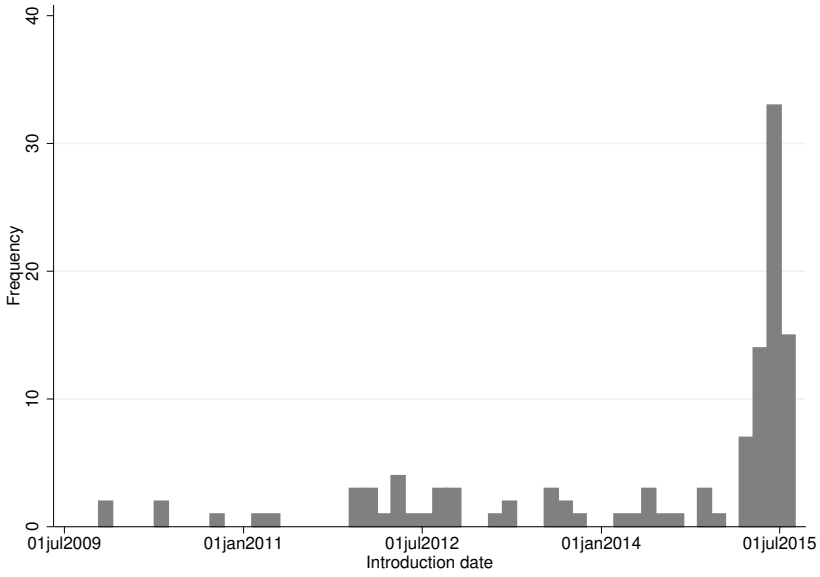



Figure A.1: Issuance of AB funds

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-to-split-and-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 Return Rates for B Funds

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.

# 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.

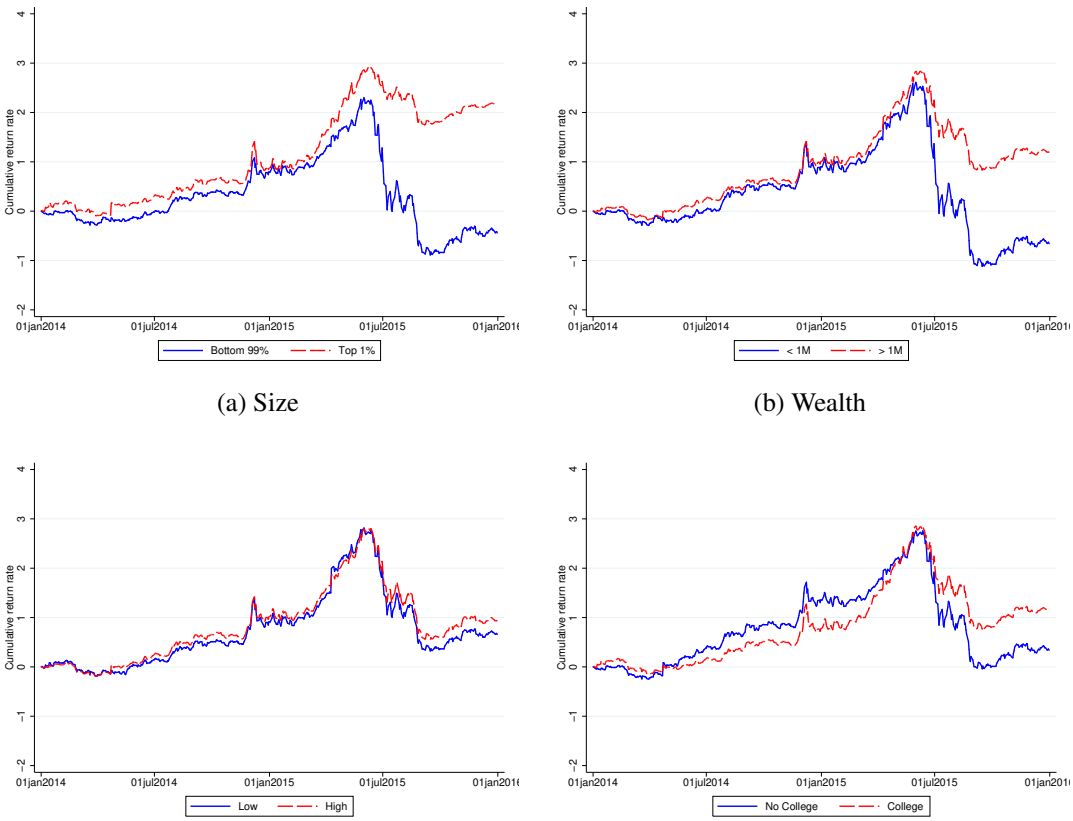
| | Run-up | Crash | Run-up | Crash | Run-up | Crash |
|---|---|---|---|---|---|---|
| Wealth (>1M) | 0.012*** | 0.056*** | | | | |
| | (0.003) | (0.009) | | | | |
| Size (top 1%) | | | 0.045*** | 0.071** | | |
| | | | (0.010) | (0.032) | | |
| Financial literacy (good) | | | | | 0.021*** | 0.055*** |
| | | | | | (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.




(a) Size

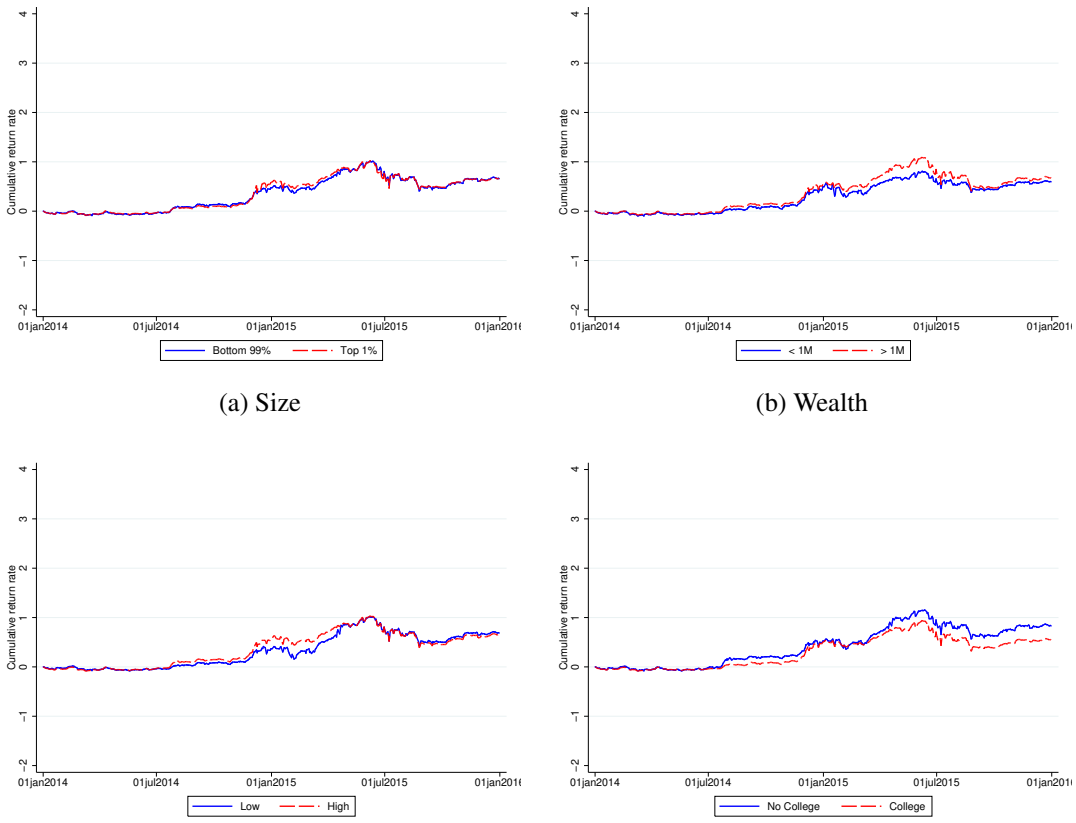
(b) Wealth

(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.

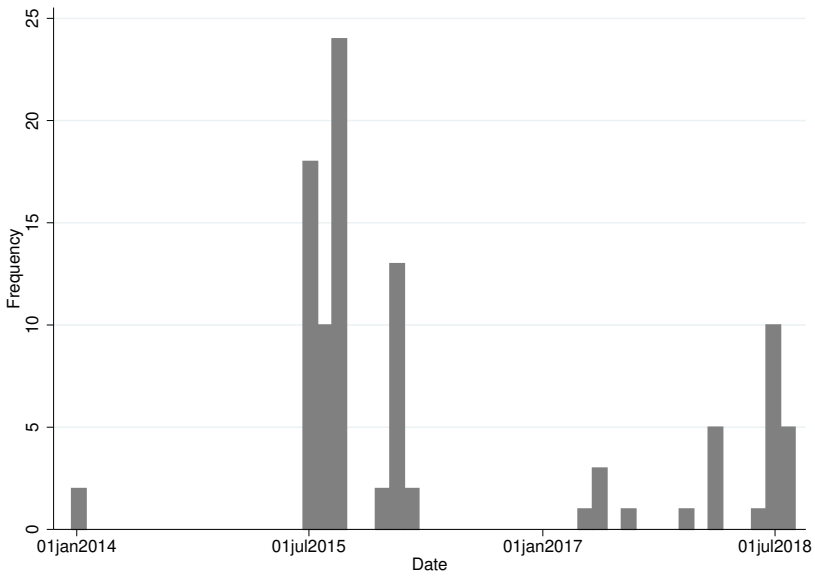



Figure A.4: Distribution of Restructuring Rvents

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 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%.

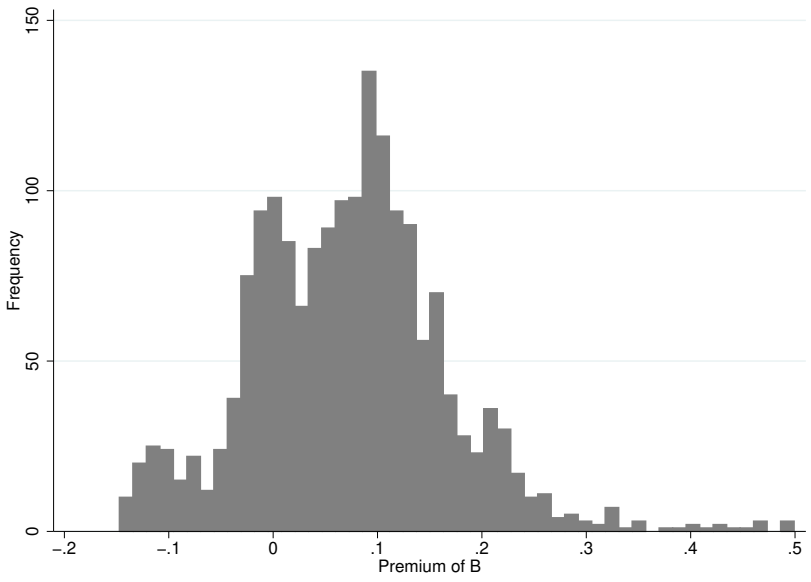



Figure A.5: Distribution of Premium

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 Expected Returns during Restructuring Events

We provide evidence that it is difficult to justify buying B funds prior to restructuring events under rational expectations. Specifically, we take the market return and volatility from historical data and calculate the expected return from investing in B funds for a risk-neutral investor. From 2006 to 2018, the annual market return was around 3% and the annual market volatility was around 26%. We take these parameter values, simulate monthly stock returns, and calculate the expected return of investing B funds for a risk-neutral investor subject to restructuring events. Table

| Event day | Leverage ratio | Expected return |
|---|---|---|
| −10 | 1.57 | 0.38% |
| −9 | 1.63 | 0.38% |
| −8 | 1.75 | 0.36% |
| −7 | 1.86 | 0.31% |
| −6 | 1.87 | 0.30% |
| −5 | 2.01 | 0.14% |
| −4 | 2.15 | -0.16% |
| −3 | 2.37 | -0.93% |
| −2 | 2.66 | -2.68% |
| −1 | 3.40 | -9.88% |
| 0 | 4.61 | -22.94% |

Table A.4: Expected returns prior to restructuring

# 10 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.5 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.5: Summary Statistics of Prospectuses

# 11 Variable Definitions

Table A.6 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.6: Definitions of Investor Characteristics