Asset Complexity and the Return Gap

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Abstract

Existing research finds that investors' returns vary with their wealth and level of sophistication. We bring a new perspective from the supply side by showing that return heterogeneity can be magnified as assets offered by the market become more complex. Using detailed account-level data, we examine the trading of B funds—complex, structured products in the Chinese market. During a three-year market cycle, the return gap between the naive and sophisticated is an order-of-magnitude greater when trading B funds than when trading simple, non-structured funds. In an event study, we confirm that this disparity is driven by differences in investors' understanding of product complexity.

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1 Introduction

Households exhibit substantial heterogeneity in portfolio choice and returns when investing in financial assets (e.g., Calvet et al. 2007; Fagereng et al. 2020). The scale of such heterogeneity and the underlying mechanisms driving it have first-order implications for household welfare and wealth inequality (e.g., Campbell 2006; Benhabib and Bisin 2018; Campbell et al. 2019; Fagereng et al. 2020). The existing literature approaches the determinants of return heterogeneity from the demand side, by showing how individual characteristics related to sophistication are important determinants of investment returns.[1] This intuition, however, is not complete without considerations from the supply side: an investor's return is determined not only by her own skill and knowledge, but also by the types of assets she can trade.

In this paper, we depart from prior literature by approaching the sources of return heterogeneity from the supply side. Our specific hypothesis is that product complexity can interact with investor characteristics to increase heterogeneity in investment performance. This is because complex products provide more opportunities for sophisticated investors to benefit from their superior investment skills and knowledge at the expense of naive investors. In other words, product complexity induces a cross-subsidy from the naive to the sophisticated—a key insight from the recent models in behavioral industrial organization (Ellison 2005; Campbell 2006; Gabaix and Laibson 2006). This mechanism is particularly relevant for complex financial products, which have been growing dramatically in market size and are owned by many households.[2] The general intuition also applies to other asset classes that are less complex but still require some financial knowledge to trade, including certain derivatives, individual stocks, mutual funds, or even some ETFs.

Alternative hypotheses, however, question the existence and magnitude of such cross-subsidies. One hypothesis, going back to Allen et al. (1994) and Duffie and Rahi (1995), is that complex prod-

[1] Campbell et al. (2019), Calvet et al. (2007), and Fagereng et al. (2020) document heterogeneity in investor performance across wealth levels, where wealth can also proxy for sophistication. Grinblatt et al. (2012) show that high-IQ investors outperform low-IQ investors. Bianchi (2017) shows that the most financially literate households outperform the least financially literate. Gargano and Rossi (2018) show that attention is positively related to investment performance. Barth et al. (2020) show that genetic endowments linked to educational attainment are linked to wealth accumulation through a facility with complex financial decision-making.

[2] For example, the market for structured products was estimated to be about 7 trillion US dollars in 2020 ("Individual Investors Get Burned by Collapse of Complex Securities," *The Wall Street Journal*, June 1, 2020). Relatedly, according to Célérier and Vallée (2017), European financial institutions have designed, marketed and sold more than 2 trillion euros of complex financial products to households since the end of 1990s, suggesting a high level of retail participation.

ucts can in fact *improve* the welfare of naive investors by expanding the set of financial products to which they have access.[3] Another hypothesis, motivated by the experimental evidence from Carlin et al. (2013), is that even when a cross-subsidy arises, it will be limited in scale because naive investors are averse to complexity and reluctant to trade complex products. The lack of consensus in theoretical work motivates an empirical analysis to understand the implications of increasing asset complexity for return heterogeneity.

We conduct such an empirical investigation in the Chinese market by examining the trades of B funds. B funds are structured products that embed leverage and are traded on the exchange. They are designed by slicing the payoffs of regular funds, typically designed to track simple indices, 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 regular fund. A funds and B 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).

Because of structuring, B funds are significantly more complex than plain-vanilla ETFs, even though both products are based on the same underlying assets. This allows us to directly compare trading of a complex product with trading of its less complex counterpart. Moreover, by focusing on exchange-traded products, we are able to separate the effect on investment performance induced by the product itself from the effect of other market participants such as issuers and brokers (e.g., Célérier and Vallée 2017; Egan 2019). Indeed, in the setting of exchange-traded B funds, brokers and issuers have little power or incentive to target naive investors.

We obtain transaction records of all exchange-traded products, including both *complex* B funds and *simple* ETFs, for almost three million Chinese investors. We supplement this data with survey-based information on investor wealth, education, and financial literacy. This allows us to examine return heterogeneity using different measures of investor sophistication and show how it changes with product complexity. Our analysis spans 2014 to 2016, a three-year window that witnesses intense trading of B funds from retail investors. Covering a full market cycle—a boom, a bust and

[3] Several recent papers challenge this argument by empirically showing that complexity can hurt investors when the seller has perverse incentives to push investors towards less desirable products (Henderson and Pearson 2011; Célérier and Vallée 2017; Vokata 2020). As we will show, we consider an exchange-traded setting without such incentives and still find evidence of complexity hurting naive investors.

a recovery—this period also allows us to examine how investors behave under different market conditions. Moreover, since the wealth transfer during the 2014–15 bubble-and-crash episode is an order-of-magnitude greater than that during other periods, the period is also quantitatively more important for welfare analysis (An et al. 2019).

Our first set of results shows that B fund returns are unevenly distributed between the sophisticated and naive. 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 two 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.[4] 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.

These results echo the conclusion from earlier work that a return gap exists between the sophisticated and naive when trading financial assets. We depart from prior literature by examining this gap through the lens of asset complexity. In particular, we show that the return gap documented above is largely driven by B funds' complex features, and we quantify the impact of complexity through two exercises. First, we examine the existence and scale of a return gap in trading nonstructured, simple ETFs. Despite the fact that both simple ETFs and B funds track the same indices, we find little evidence of a wealth transfer across investor groups in the case of ETF trades during the same period. Even when one group outperformed, the return difference was an order-of-magnitude smaller than the return difference seen in trading B funds. This is consistent with our hypothesis that the scale of cross-subsidization is magnified by asset complexity.

Second, using an event study, we establish a direct link between the documented wealth trans-

[4]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.

fer and one particular complex feature of B funds: the inclusion of restructuring clauses. Restructuring clauses are triggered when the NAV of a B fund drops below a pre-specified threshold. Importantly, the triggering of these restructuring clauses implies a sharp decrease in the market value of B shares.[5] Therefore, when the NAV gradually approaches the threshold, the dominant strategy is to start pulling money out of B funds to avoid the eventual loss in market value caused by restructuring. In fact, even after restructuring is triggered, trading would continue for an additional day, giving traders ample time to respond. At this point—regardless of risk preferences or beliefs—investors should have liquidated their B fund positions. These implications, while important, may not be fully understood by an average retail investor. Although restructuring clauses are explicitly stated in prospectuses, they are complex and not easy to understand. A full grasp of the wealth implications of restructuring clauses requires further understanding and frequent monitoring of the market. As a result, naive investors may have an incomplete understanding of restructuring events, causing them to make suboptimal decisions.

We study investors' trading behavior and performance in the market of B funds during the 2015 market crash, during which almost half of the B funds went into restructuring. 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, despite 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 performed much better: they were able to reduce their exposure to B funds right before restructuring events took place. Overall, 25% to 45% of the total wealth transfer can be directly attributed to investors' different responses to restructuring events.

We provide further evidence consistent with our proposed mechanism that sophisticated investors's superior performance derives from their better understanding of the product's complex features.[6] First, 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. Second, in the later restructuring waves, investors who had held when prior restructuring

[5]We will discuss the reasons for this in detail later in the paper. In short, it has to do with the closed-end fund premium, which results from the underlying leverage, and the exchange's trading rules.

[6]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.

events took place performed substantially better, suggesting that they learned from past mistakes. Therefore experiences, especially experiences of losses, can help investors learn about asset features. However, this learning comes at the cost of many investors suffering financial losses, and policymakers should also think about ways to protect and educate new investors who do not understand the full features of the asset. We argue that more tailored financial education (Bu et al. 2021) or robo-advising (D'Acunto et al. 2019; D'Acunto and Rossi 2021) could prove valuable.

More generally, for our mechanism to have a first-order impact on return heterogeneity within an asset class, two conditions are required. First, the asset must be sufficiently complex so that there is enough room for cross-subsidization. For products that are simple, the optimal path of trading does not require attention, learning, or advice from others, and this low threshold puts naive investors and sophisticated investors on equal footing. Second, the asset must be packaged in a way to appear simple, so that it attracts naive investors who think that they understand the product well and simply ignore the complex features. These conditions apply not only to the Chinese structured funds we study, but also to many structured products.[7]

Finally, to shed light on the decision process of naive investors, we examine *why* these products were so popular. We show that investors buy B funds as they chase high returns and ignore hidden risks. Most new investors were extrapolators who entered soon after the market experienced a large positive return (Shin 2019). Therefore, investors were attracted by the high "headline" returns delivered by leveraged B funds during the market boom, but overlooked the negative consequences that could result from the funds' complex features during a crash, in a way described by Bordalo et al. (2016). These products were popular despite trading at a significant premium to their net asset value. Such a trading frenzy mirrors the recent episodes associated with the rise of "meme" stocks like GME, AMC, and Hertz: drawn in by incredible returns, retail traders bought these stocks even when they had little understanding about the current state of the firms and how their prices could be completely detached from firm fundamentals. Many, in the end, suffered losses.[8]

[7]For example, consider the USO ETF—an ETF based on oil futures, which has billions of dollars in AUM. Unsophisticated investors may see this and, interested in betting on the price of oil to increase, buy the product. Sophisticated investors may take a closer and see that these futures contracts will need to be rolled over towards the end of the period. If the oil market is in contango (backwardation), sophisticated investors will realize that the rollover of these contracts will likely entail losses (gains). We think there is a clear parallel here between restructuring events for B fund shares and rollover events for the USO ETF.

[8]For example, in his January 24th, 2022 Money Opinion newsletter, Matt Levine notes that "a lot of the memeiest and most retail-driven parts of the market have actually been underperforming since last February, 'the retail crowd

Our study contributes to the literature on individual investor performance heterogeneity. The existing studies approach the determinants of performance heterogeneity from the demand side and find individual characteristics such as wealth, financial literacy, IQ, and attention to be key drivers (e.g., Campbell et al. 2019; Calvet et al. 2007; Fagereng et al. 2020; Grinblatt et al. 2012; Bianchi 2017; Gargano and Rossi 2018; Barth et al. 2020). We approach this question from the supply side, by showing that product complexity magnifies return heterogeneity induced by differences in individual characteristics. This suggests that the features of financial products available to trade may be a driver of return heterogeneity and, consequently, wealth inequality.

We also contribute to the empirical literature on the welfare implications of complex products (Henderson and Pearson 2011; Chang et al. 2015; Célérier and Vallée 2017; Calvet et al. 2020; Vokata 2020). Unlike earlier papers, which typically focus on the effect of complex products on an average investor, we study heterogeneous effects and redistributional consequences. Importantly, by using an exchange-traded setting, we are able to demonstrate that complex products can still harm naive households in the absence of perverse incentives from brokers and issuers. Instead of being exploited by brokers or issuers, naive households lose money trading complex assets on an exchange. 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).

Our results have implications for policymakers, who must balance the benefits of protecting naive investors from risky financial products with the costs of regulating more sophisticated households (Campbell 2016). We contribute to the debate on this tradeoff by highlighting the dangers of exchange-traded complex products. The exchange-traded setting of our study is especially pertinent for the regulation of markets with new complex assets.[9] The introduction of Chinese structured funds filled 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 enough about the products' features. Following this episode, the Chinese regulators halted the issuance of new structured funds and placed a higher barrier to entry, largely

has been badly lagging the S&P 500 for a while now,' and 'the whole 'Reddit vs. Hedge Funds' meme that came out of the GameStop story really did turn out to be the peak of the mania.'"

[9]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). Gary Gensler, the SEC chairman, recently called for studying the danger of exchange-traded complex products ((https://www.sec.gov/news/public-statement/gensler-statement-complex-exchange-traded-products-100421#_ftn1).

due the negative consequences documented in this paper.

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 our work is Li et al. (2020), which documents performance heterogeneity among warrant traders and attributes 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 that liquidity provision plays 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.

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, an interest-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. On subsequent days, the parent share and B share NAV are calculated at the end of every trading day based on the market value of the underlying assets. A shares receive interest 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 open-end mutual fund shares, parent shares can be created or redeemed at the NAV through brokers and are typically *not* traded on the exchange.[10] In contrast, A and B shares are traded on the exchange and cannot be directly created or redeemed through brokers. As a result, the standard arbitrage mechanism through creation and redemption is not at work.[11] Instead, the main arbitrage mechanism—the so-called "create-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 to NAV, 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. We discuss the significant limits to this arbitrage mechanism in Section A.4 of the Online Appendix.

Trading from retail investors concentrated on the equity-linked B funds, to which the bulk of our subsequent analysis is devoted.[12] 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.

2.2.1 Feature I: time-varying leverage

Unlike a standard levered fund, which rebalances daily to maintain a constant leverage ratio, AB funds do not engage in daily rebalancing and B's leverage ratio is time-varying. Below, we

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

[11]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.

[12]We include a brief discussion of A funds in Section A.14.2 of the Online Appendix.

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. We normalize the NAV of the parent such that it equals one. This implies that the following identity will always hold: $NAV_B + NAV_A = 2 \times NAV_P$. Assume, for simplicity, that the interest rate paid to A is zero. Table 2 shows how changes in P's NAV affect the embedded leverage. When P rises in NAV, B also rises in NAV, reducing leverage; conversely, when P drops in NAV, B also drops in NAV, 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 rather than delegate the task to fund managers.

Month	NAV_P	NAV_A	NAV_B	Leverage (NAV_A/NAV_B)
3	1.1	1.0	1.2	0.83
6	1.3	1.0	1.6	0.63
9	0.8	1.0	0.6	1.67
12	0.6	1.0	0.2	5.00

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. To understand why restructuring clauses were included in the first place, notice that without putting in any extra clauses, the A tranche is not risk-free. In the earlier example, since the NAV of B is bounded at zero and $NAV_B + NAV_A = 2 \times NAV_P$, whenever P's NAV falls by more than 50 percent, the losses will result in the A's NAV falling below one. That is, any additional losses beyond 50 percent for P will be reflected in the NAV of A because B shares cannot have a negative NAV. In the last row of Table 2, when P's per-share NAV drops by 40% to 0.60 in month 12, it puts A on the edge of losses. To ensure that the A tranche is risk-free, once the per-share NAV of the B tranche falls below a certain threshold—typically at 0.25—it automatically triggers a restructuring process.

During restructuring, old A and B shares are pooled and new shares of A, B, and P are created and redistributed. We explain the procedure by returning to the last row of Table 2 when the per-share NAV of P falls to 0.60 and triggers restructuring. After pooling, the total NAV of the underlying assets equals 120. Based on these assets, 20 shares of A, 20 shares of B, and 80 shares of P are newly created, all at the per-share NAV of one. The 20 new B shares go to the old B fund shareholders: each receives new B shares equal in NAV to their pre-restructuring position, a process that is similar to a reverse share split. The 20 new A shares and 80 new parent shares are similarly distributed among the A fund shareholders on a pro rata basis. For example, if an investor was holding 10 A shares prior to restructuring, they would be holding 2 new A shares and 8 new P shares afterwards. Figure 1 illustrates the process visually. It is important to note that, while the restructuring process does not redistribute the asset payoffs between A and B fund shareholders, it does alter the embedded leverage of B shares: post restructuring, the embedded leverage of B shares dramatically decreases from five to one. We explain the timeline of restructuring events in greater detail in Section 4.

2.2.3 Comparison with other structured products

In the U.S. 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 U.S. (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.[13] In our setting, structured funds are made complex by the embedded time-varying leverage and various restructuring clauses.

We note a distinctive feature of our setting. Previous studies mostly analyze the interaction between brokers and households in markets for illiquid financial products. Because the fee structure compensates brokers more for selling inferior products, brokers tend to use their market power and screening mechanism to target naive households (Egan 2019; Vokata 2020). In comparison, in the exchange-traded setting we consider, brokers have neither the incentive nor the power to target an

[13] 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).

investor group. Brokers charge a flat fee rate for all exchange-traded funds and stocks and there is no monetary incentive for them to sell inferior products. The exchange-traded setting allows all investors to trade structured funds freely, which means that brokers cannot preclude some investors from accessing the product. This feature 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 (Bian et al. 2021; Liao et al. 2021). Figure 2a 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 in our sample were trading them.

2.3.1 Market size

For a financial product to have a material impact on a household's financial wealth, it needs to constitute a sizable part of the household portfolio. Figure 2b 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.[14] Table 3 shows the monthly distribution of B funds' portfolio weight among investors with a positive balance of B shares. For an average (median) investor, B funds constituted 32% (14%) of her equity holding.[15]

[14]See Section A.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.

[15]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

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.[16] 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 3 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 together in the time-series, with a correlation coefficient of 0.52.

The strong relationship between leverage and the premium holds not only in the time-series but also in the cross-section of funds: funds with a higher leverage were associated with a higher premium. Here we summarize the cross-sectional results, which are detailed in Section A.3 of the Online Appendix. In short, 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, the evidence strongly supports the claim that the variation in the B premium was mostly driven by the embedded leverage.

The B premium was large and persisted for a long time, so why didn't the arbitrageurs step in and correct the mispricing? There were significant limits to arbitrage, as discussed in Section 2.1. Because arbitrageurs could not directly create new B shares on the secondary market, arbitrage

market held by mutual funds was very small (less than 5%) during this period.

[16]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.

activity required them to create new parent shares first and split them into A and B shares for sale on the secondary market. However, the entire process took at least two days to complete and would subject arbitrageurs to various other risks (Shleifer and Vishny 1997). Moreover, A shares were substantially underpriced, as Figure 3 shows, trading at a discount more than 15% at one point.[17] This means that even if the entire arbitrage trade was completed successfully, it may not as profitable as desired as arbitrageurs would have to sell A shares at a discount. Indeed, although the combined price of A and B shares remained close to the underlying assets' fundamental value, both A and B were substantially "mispriced."

Restructuring events. Again, to ensure the low-risk feature of A funds, B funds had restructuring clauses to reset leverage when their NAV dropped below a preset threshold. While the threshold was set at such a low level 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—to enter a restructuring process.[18] Many funds were forced to reset their leverage back to one, and the associated premium vanished afterwards. The disappearance of the B premium had important implications for investor welfare, as investors holding B funds during restructuring would find the market value of their B positions substantially reduced. 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

[17] We speculate on the source of this discount later in Section A.14.2, but acknowledge that a detailed investigation of it is beyond the scope of this paper.

[18] In Section A.10 of the Online Appendix, Figure A.7 plots the distribution of all restructuring events from 2014 to 2018 and shows that most are concentrated in the 2015 market crash.

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 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 A.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 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 4 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 overweight 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.[19] Panel A shows RMB returns. Consistent with Figure 4, 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. These losses are substantial. For example, among investors whose annual income is below 100K RMB, the average loss is 21,831RMB, more than 20% of their annual income. Across the entire episode, these investors lost 9,612 RMB - more than 10% of their annual income.

To further examine B returns across investors by controlling for investment size, Panels B to D present summary statistics for return rates, which are calculated by dividing RMB returns to investment size. We measure each investor's investment size in three ways based on the account's daily B fund balance: maximum balance, average balance, and maximum investment size, which is calculated as the sum of the initial B fund balance at the beginning of each sub-period plus the maximum cumulative net RMB flow into B funds during that sub-period. Unsurprisingly, return rates, on average, are positive during the quiet and run-up periods and negative during 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 so-

[19]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.

phistication and an important consideration in studies of wealth inequality, but we also consider other proxies for sophistication.

3.2.1 Wealth

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; in Section A.6 of the Online Appendix, we consider finer cuts and find robust results.[20] 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 5 plots cumulative RMB returns and return rates for wealth groups, where cumulatve return rates are calculated by dividing cumulative RMB returns to the average amount of investment to date. 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. Figure 5a 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.[21] Similarly, Figure 5b 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 throughout 2016.

The gap in returns primarily stems from the crash. In Figure 5a, 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.

[20] Specifically, we sort investors into four groups: top 1%, 91–99%, 81–90%, and below 80%. We show a monotonic pattern in RMB returns and return rates from the least to the most wealthy group.

[21] 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.

We see a similar pattern in Figure 5c for return rates. Due to differences in initial investment, this pattern is less observable in Figure 5b, which concerns RMB returns. Figure 5d, however, shows a similar pattern when RMB returns are normalized based on investment size.

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, and 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, and we sort investors into two groups based on whether they have earned a college degree or not. Figure 6 plots returns for investor groups sorted on their levels of financial literacy and education. As in Figure 5, 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 Figures 6c and 6d. 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

The bulk of our empirical analysis is devoted to the overall wealth transfer across groups because we are interested in examining the macro-level effects of B funds. Investor-level regressions, in which all investors are equal-weighted, make little distinction between those who made a nominal one-time trade and those who actively trade large sums of money. However, it is still interesting to explore equal-weighted investor-level effects. 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 A.7 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 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.[22] 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. We point out that the magnitudes here are much smaller than before because the analysis equal-weights all investors.

3.3 Comparison with simple 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 perhaps 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 designed by redistributing the cash flows from a pool of mortgages, structured funds are similarly designed by slicing the payoffs from traditional ETFs. A second desirable feature of ETFs, as shown in Figure 2b, 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 7 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.[23]

Figure 8 plots total RMB profits for different investor groups. To make an appropriate compar-

[22] It is also important to note that the crash window is about half as long as the run-up window, which makes the return gap increase even more striking. Additionally, in Table 7, we find that the return gap between the sophisticated and naive during the run-up was similar in B funds and ETFs. During the crash, it was very different.

[23] In the Online Appendix, Table A.4 compares investor characteristics across three investor groups: those who only traded AB funds, those who only traded ETFs, and those who traded both. Overall, we find that investors who traded AB funds are less wealthy and have a small account, are younger and less experienced with investing in the stock market, are less likely to have a college degree or higher, and have a lower self-reported financial literacy.

ison with the previous results, all figures are plotted using the same scales as in Figure 5. Looking at the graphs is sufficiently telling: in most figures, the scale of wealth transfer, if any, is barely visible. In Figure 8a, small investors actually make more profits than large investors due to a greater initial investment. In Figures 8b and 8c, the direction of the transfer is consistent with that for B funds, but the magnitude is much smaller. In the Online Appendix, Figure A.4 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 5 and 6.

Table 7 puts all the four variables considered so far in the same regression and additionally controls for gender and experience.[24] In Columns 2 and 3 of Panel A, wealth, size, and financial literacy are all positive determinants of B fund returns during the crash. In comparison, in Columns 6 and 7 of Panel B, only financial literacy is a positive determinant of ETF returns. For example, during the crash, investors in the top 1% of account size earned about 3% higher returns trading B funds, but not higher returns trading ETFs, than other investors. Finally, as shown in Column 4, the results about B fund returns 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 8 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 5a. Second, as shown in Figure A.4, 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 track some underlying equity indexes, the two

[24] This regression is equal-weighted and, therefore, will not speak directly to overall macro wealth transfers.

asset classes are very similar in the types of stocks they cover. However, there are a few exceptions where the equity index tracked 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 A.9 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.

In Figure 9, Figure 9a plots the evolution of B fund 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.[25]

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 phenomenon ex-ante. What knowledge and understanding were required for them to make this prediction? Below, we discuss several sufficient conditions under which investors could rationally expect a reduction in the premium.

The first condition requires investors to understand the *economic* relationship between the premium and leverage and know about the leverage reset during a restructuring event. Given the restrictions to obtain leverage to Chinese retail investors, they may have been able to infer a demand for products that offer leverage indirectly. As both B price and NAV were directly observable, it was straightforward to calculate premium and leverage to confirm this economic relationship. Investors also should have been able to anticipate a leverage reduction from restructuring since (i) restructuring clauses were stated in prospectuses and (ii) investors received reminder notifications from their brokers when the NAV approached the threshold.[26] Therefore, investors should expect a premium reduction after restructuring events.

The second condition does not require investors to understand the economic relationship. Rather, it requires investors to observe the *statistical* relationship between the premium and leverage and infer an economic relationship. Given the positive relationship, investors should expect a reduction when restructuring reduces the leverage ratio to one. Relatedly, investors could rationally expect a reduction in premium by examining premiums of funds with a leverage ratio close to one. To show this, we examine all instances in which a fund was trading at a leverage ratio close to one prior to the crash.[27] 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.

[25] We describe an example of one of these restructurings in detail in Section A.5 of the Online Appendix.
[26] In the Appendix, we describe how restructurings are detailed in the prospectuses.
[27] The overall distribution of the B premium is included in Section A.11 of the Online Appendix.

The third condition does not even require an understanding of the relationship between the premium and leverage: as long as investors understand the embedded leverage and the trading rules imposed by the exchange, they should rationally expect part of the premium to disappear. To see this, notice that 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 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 Figure 9b, 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. It is important to note that recognizing the rational course of action would require significant attention and analysis—we would only expect sophisticated, attentive investors to be able to make this inference.

4.3 Trading behavior around restructuring

How did investors actually respond to restructuring events? Figure 10a 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 9b 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 Figure 10a 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, Figure 10b plots the post-event retail flows and returns, where the event is defined by the first time a fund drops below 0.35.[28] 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

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

historical data and calculate the expected return from investing in B funds for a risk-neutral investor; details are included in Section A.12 of the Online Appendix. As B funds approach the threshold, the heightened risk of restructuring substantially biases 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

Section 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?

Figure 11 shows the cumulative trading flows during the 21-day window around the event day for investor groups sorted on measures of sophistication. In Figure 11a, 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. Figures 11b to 11d show similar patterns, albeit with a slightly smaller magnitude. For instance, in Figure 11c, 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 5 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 5a, 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 suffering 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.[29] Figure 12a documents how trading behavior around restructuring events 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 experience trading B funds. Figure 12b 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 Alternative Explanations

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.

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

Theories based on non-traditional preferences can also be evoked to explain the different trading patterns. One candidate is a gambling preference, or demand for positive skewness: naive investors may be more prone to prospect theory preferences, apply high decision-weights to low probability outcomes and bet more on an eventual resurrection. Three pieces of evidence cast doubt on this as the sole explanation of our results. 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 an innate preference driving behavior. Second, as discussed above, while prospect theory preferences could explain increased holdings prior to restructuring, it cannot explain why some investors increased their holdings on day 1. As we argue in Section 4.7, we think that gambling preferences contribute to the desire for these products before restructuring, but we would also need to evoke bounded rationality to explain the body of results.

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 (D'Acunto, Hoang, Paloviita, and Weber (2020)), then they are more likely to get out before structuring events as B shares keep dropping in price or NAV. 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. Furthermore, extrapolation has little explanatory power for trading behavior around restructuring events, although it explains the initial entry decisions very well.[30]

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

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

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. Figures 13a and 13b plot the returns of liquidity providers and non-liquidity providers, respectively, and show 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 holdings at the brokerage accounts to examine their liquidity needs. Figure 14 plots these patterns from 2014 to 2015. Figure 14a 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 14b: 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. Figures 13c and 13d plot the returns for high- and low-disposition-effect investors. The two groups exhibited similar returns from 2014 to 2015. Figure 13e 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 Figure 10a.

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. Figure 13f 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. Overall, our results suggest that the ostrich effect could prove costly when investors trade assets with complex features, as they require more attention and more frequent monitoring. However, our results also suggest that attention is not always good: when investors are ill informed, more attention could lead to even bigger mistakes.

4.7 What explains this pattern of behavior?

We argue that the most likely explanation for why the unsophisticated did not liquidate 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, in conjunction with bounded rationality, explain this increase: gambling preferences and borrowing constraints. In fact, these explanations may be complementary: gambling preferences 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 preference.[31] Figure 15a shows that, consistent with gambling preference, investors who have traded warrants increased their holdings more prior to restructuring. We want to emphasize that gambling itself may not necessarily be irrational; in many cases, investors may be rationally betting on an eventual resurrection. For instance, during the Hertz bankruptcy, some investors ended up making money by purchasing Hertz shares that were thought to be worthless. In our case, however, gambling is almost surely irrational, and investors gambled not only because of their preferences but also because of their limited knowledge and lack of sophistication.

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 Figures 15b and 15c, we find that constrained investors, using each identification method, increased their holdings more than unconstrained investors prior to restructuring.

5 External Validity and Policy Implications

5.1 External validity

In this subsection, we discuss the conditions under which the cross-subsidy mechanism we study can have a first-order impact on return heterogeneity. In our view, at least two conditions are required. First, the asset must be sufficiently complex. Complexity can take different forms: numerous clauses detailing the various conditions that may affect the eventual return, overly complicated relationships between risk and return, or hidden fees. For example, in our setting of Chinese structured funds, the inclusion of restructuring clauses affected expected returns and risk, but the implications were not obvious to all traders. Indeed, the implications of restructuring were

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

only apparent to those who paid close attention and studied the underlying details, or those who relied on the advice of other, more sophisticated investors.

Second, the asset is packaged in a way to appear simple, so that it attracts naive investors who think that they understand the product well. While the asset should appear simple, it must also have salient features that are attractive for naive investors. In our setting, B funds had attractive and unique leverage features. Still, their leverage features can not be the sole explanation for their popularity because B funds only became popular after a few years of existence. Below, we show that their popularity was primarily driven by the higher returns they delivered in the run-up. In particular, extrapolative 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 a measure of extrapolation.[32] 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. Overall, the evidence is consistent with the idea that it was the salient upside that lured naive extrapolating investors with gambling preferences into the market.

5.2 Policy implications

Our evidence shows that, lured by leverage and high past returns, many investors bought B funds despite not knowing how to navigate restructuring events. This should motivate regulators to consider higher barriers to entry such that it is more likely for investors to be aware of the dangers. This recommendation is particularly relevant for products with high embedded downside risk, but little realized downside risk. Such products often appear quite attractive—they usually have salient high realized returns without any significant negative returns—but they also have a hidden risk that is difficult to understand. This may lead naive investors to purchase when the embedded risk is heightened because they don't understand the true underlying risk. These types

[32] Our measure of extrapolation is the weighted average, based on purchase sizes, of purchased firms' past one-month returns.

of products are also more likely to generate a return gap since the sophisticated can better navigate these embedded risks than their unsophisticated counterparts.

Our results also suggest limits to the value of disclosures. Restructurings, and the underlying processes, were clearly disclosed in filings, yet, investors still suffered from these episodes. However, this does not mean that these disclosures are without merit. We encourage policymakers to consider ways that the risks in these disclosures can be effectively communicated to unsophisticated investors. One avenue this could be communicated is through robo-advisers (D'Acunto et al. 2019; D'Acunto and Rossi 2021). Indeed, policymakers should explore the potential of these tools to simplify the messages of disclosures in a salient, accessible way to investors. Our results on learning suggest that unsophisticated traders can improve rather quickly with feedback from the market. Experiences, especially experiences of losses, can help investors learn about asset features. However, this learning comes at a significant cost for new investors. Policymakers should consider ways to protect and educate new investors who do not fully understand an asset's features. Our learning results suggest that an experiential financial education could prove valuable (Bu et al. 2021).

6 Conclusion

The sources of return heterogeneity in financial markets are important considerations for policymakers when analyzing issues on market regulation and wealth inequality. While there is a growing literature that studies how various individual characteristics empirically relate to investment performance, we study return heterogeneity from the supply side. We argue that the types of products offered may contribute to return heterogeneity across different levels of sophistication. Indeed, we show that the return gap between the sophisticated and naive can increase with product complexity. This highlights the dangers of increasing product complexity for investor welfare and wealth inequality.

Our results also have implications for the regulation of complex financial products. In theory, complex financial products can be welfare improving. With perfectly rational investors, complex products can better distribute risk than their simpler counterparts. Existing evidence shows that issuers and brokers can use complexity to enrich their coffers by tricking naive investors into buying products at inflated prices. We show that the dangers of complex products to the naive extend beyond issuance and broker influence. Specifically, we show that, even in a setting devoid of such perverse incentives, the naive 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. Future work should examine whether regulation, training (Bu et al. 2021), or robo-advising (D'Acunto et al. 2019; D'Acunto and Rossi 2021) can address the dangers of complexity for the unsophisticated. We offer a particularly important lesson about products with unrealized crash risk. Since extrapolation explains B fund purchases, it is reasonable to assume that investors are paying attention to the return history. If this is the case, 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.

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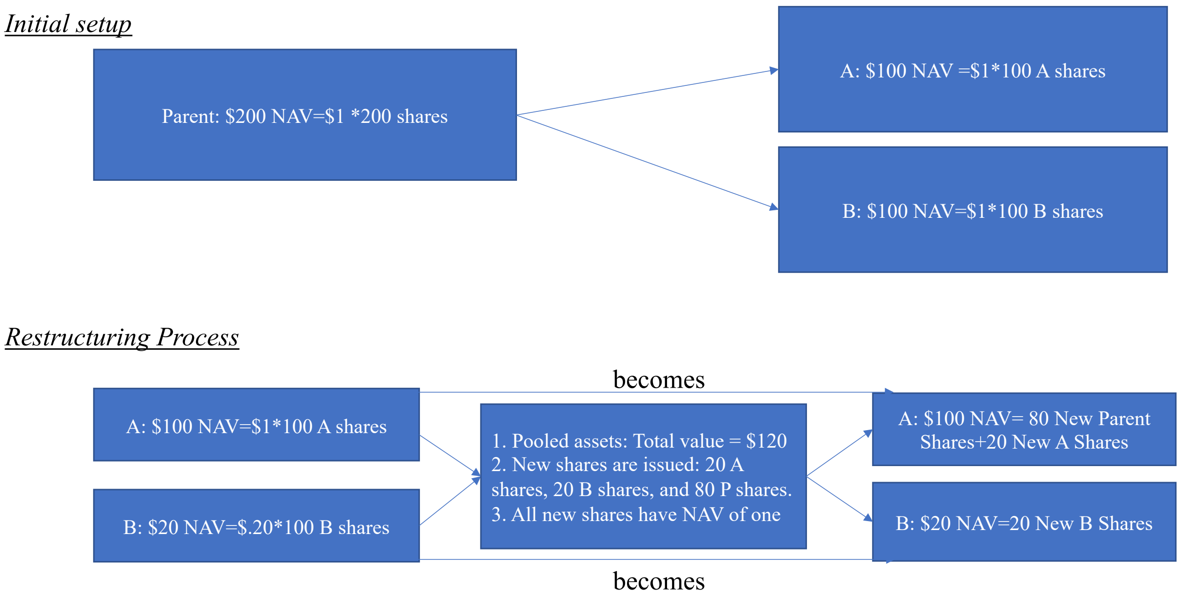
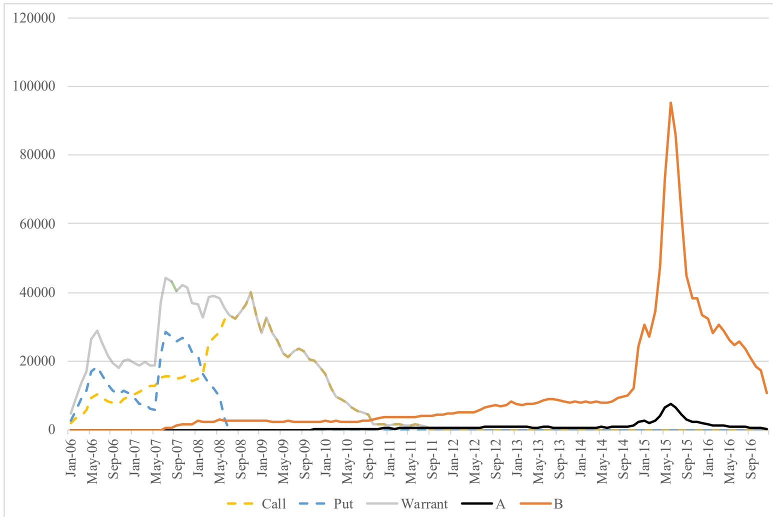
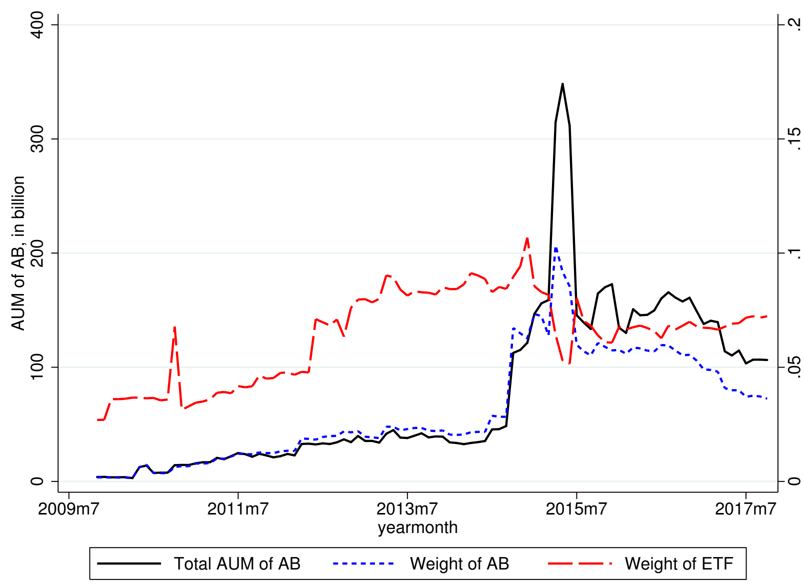


Figure 1: Restructuring Process

Note: The figure offers an example of how A and B shares are restructured after a restructuring clause is triggered.



(a) Popularity



(b) Market size of structured funds

Figure 2: Popularity and Market Size of Structured Funds

Note: Sub-figure 2a 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 2b 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.

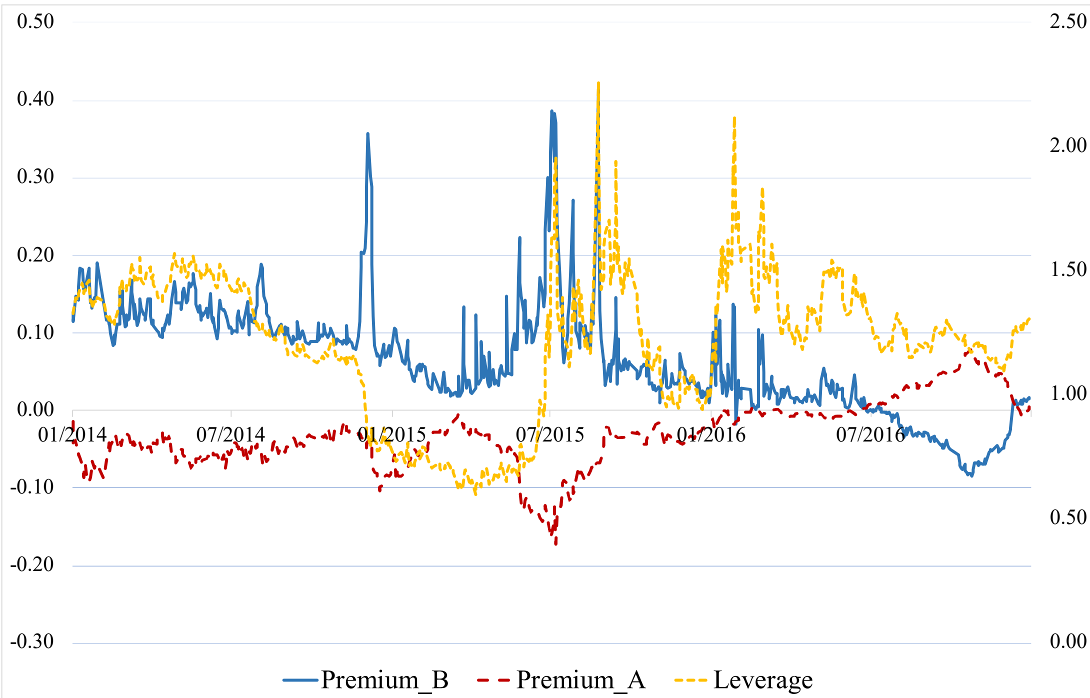


Figure 3: Time-series Variations of Leverage and Premium, 2014–2016

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.

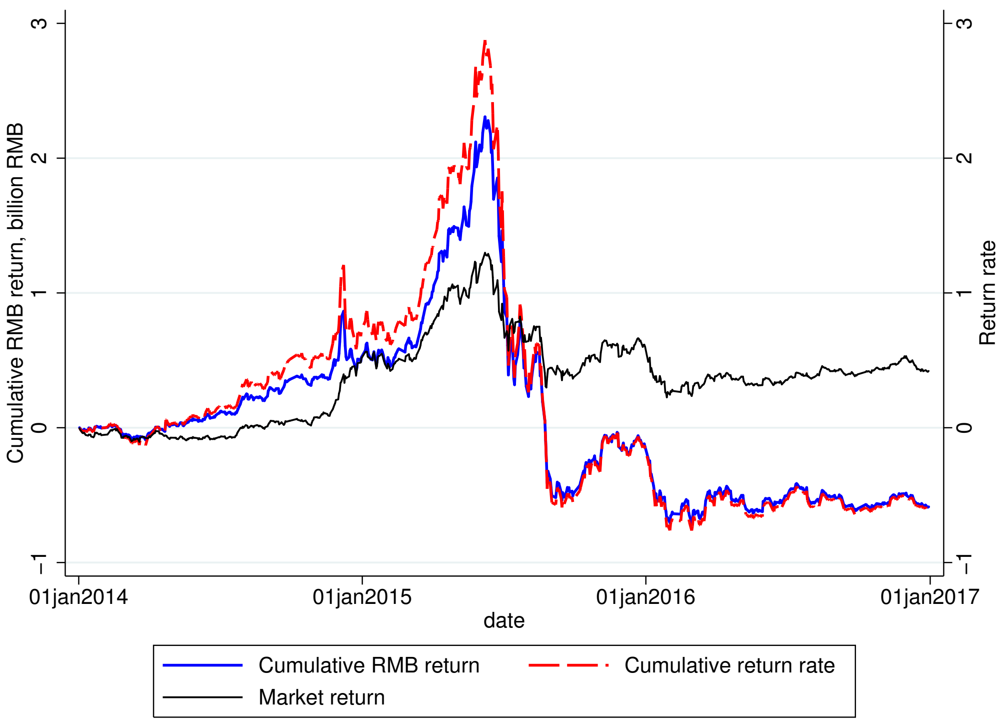
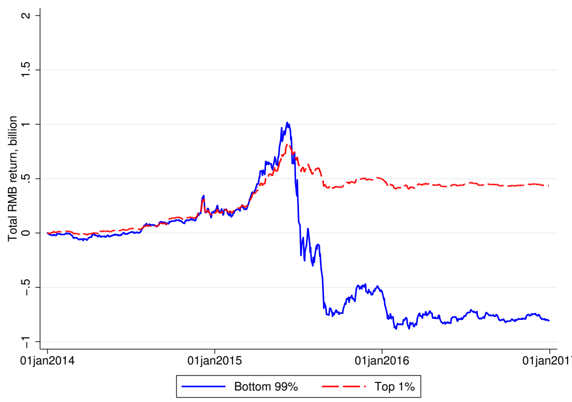
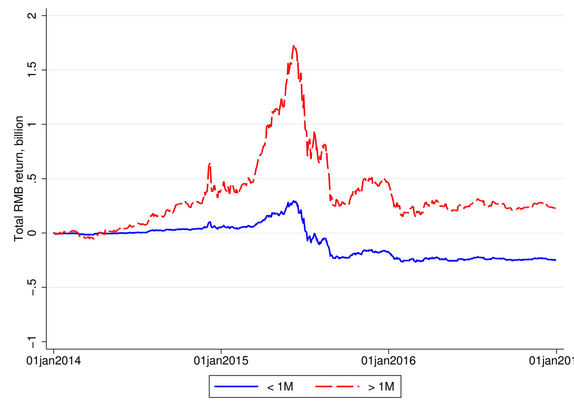


Figure 4: Cumulative Returns and Trading Flows of B Funds, 2014–2016

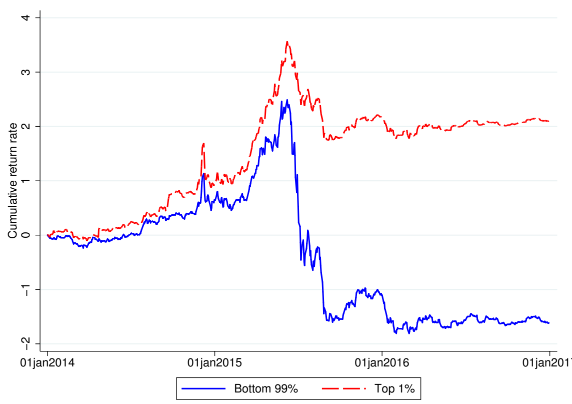
Note: Cumulative returns and flows from B funds from 2014 to 2016. The blue solid line represents the cumulative RMB return from trading B funds. The grey bar represents the cumulative trading flow into B funds. Both series are scaled using the left axis. The red dashed line represents cumulative return 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

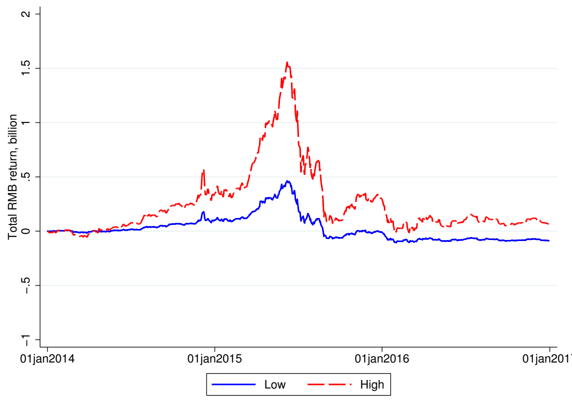


(c) Return rates for size groups

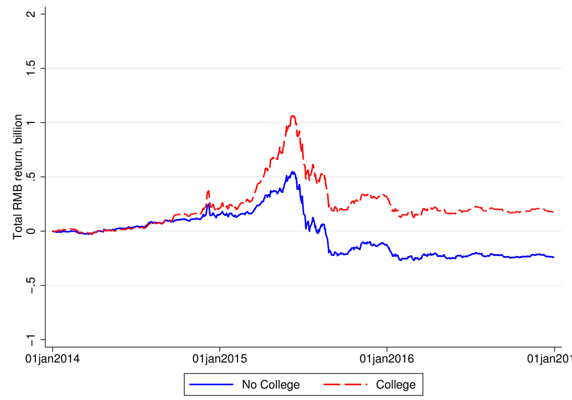
(d) Return rates for wealth groups

Figure 5: 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.

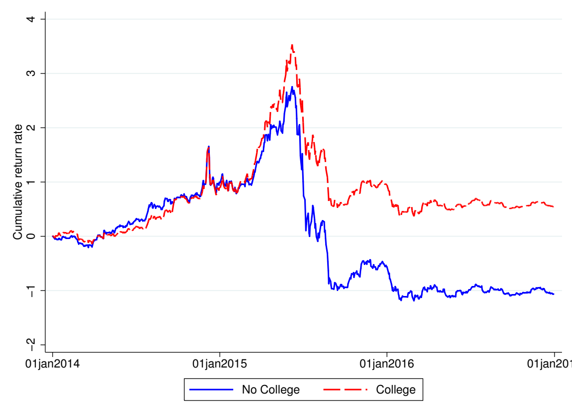


(a) RMB return for literacy groups



(b) RMB return for education groups

(c) Return rates for literacy groups



(d) Return rates for education groups

Figure 6: 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.

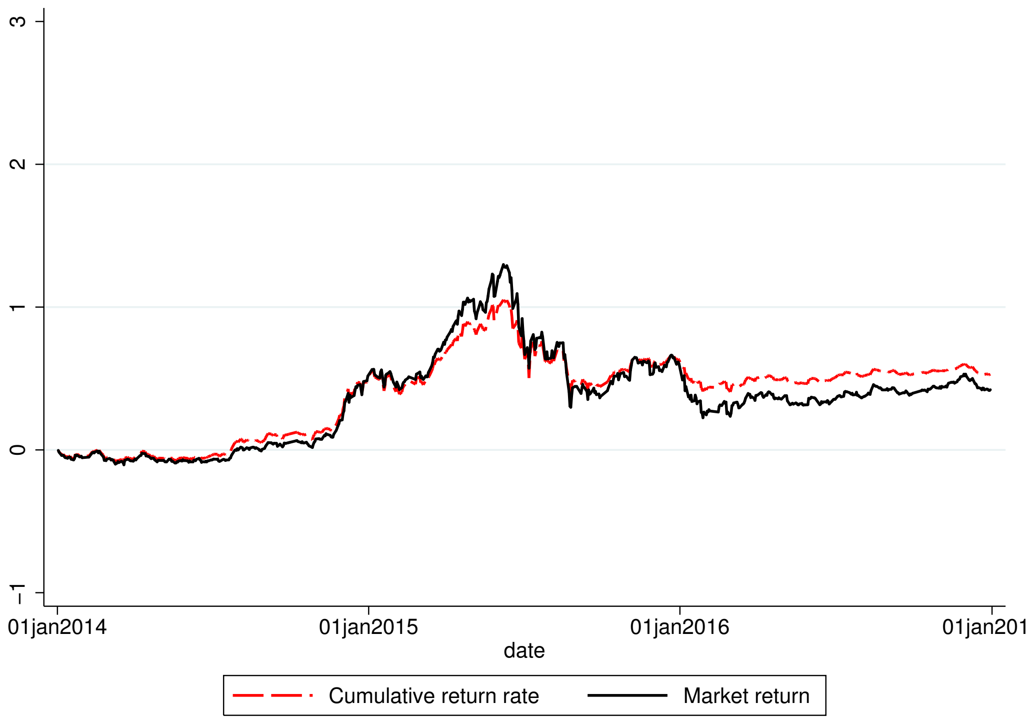
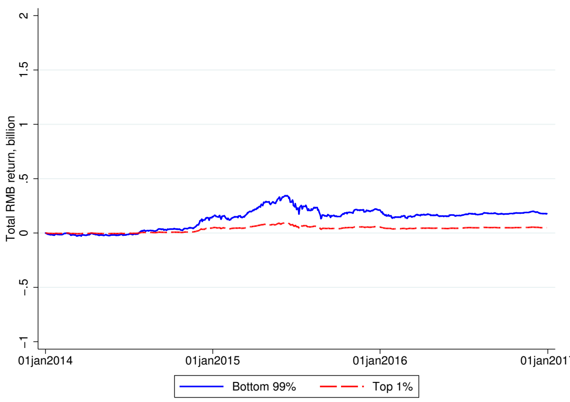
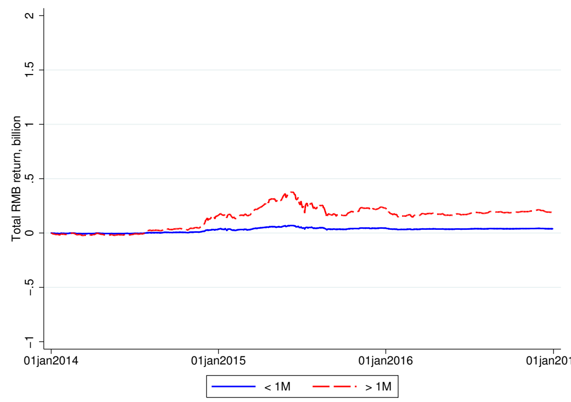


Figure 7: Cumulative Returns from ETFs, 2014-2016

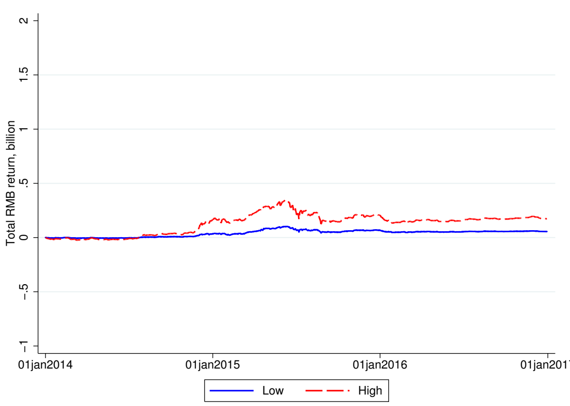
Note: This figure plots cumulative returns and flows from ETFs from 2014 to 2016. The red dashed line represents the cumulative return rate, calculated by dividing cumulative RMB return by average investment. The black solid line represents the market return.



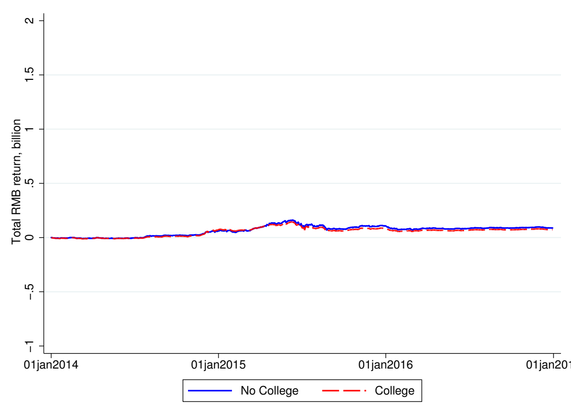
(a) Size



(b) Wealth



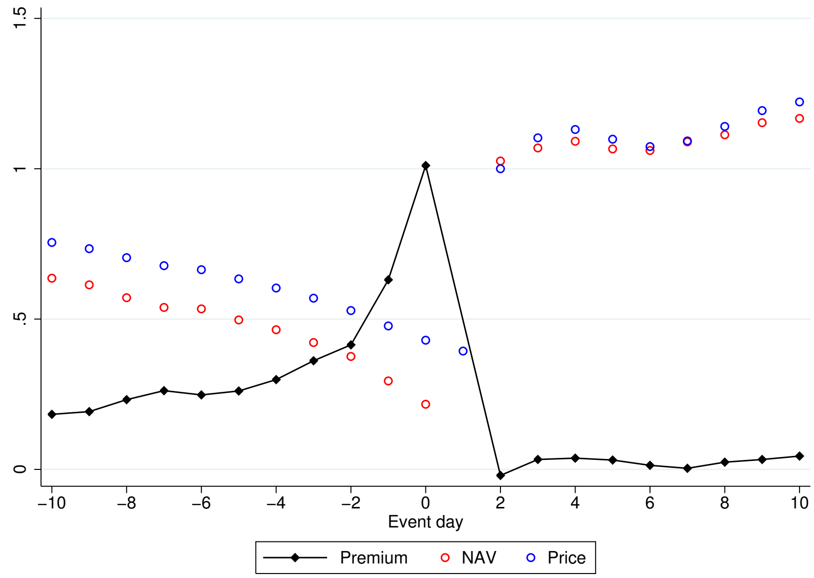
(c) Literacy



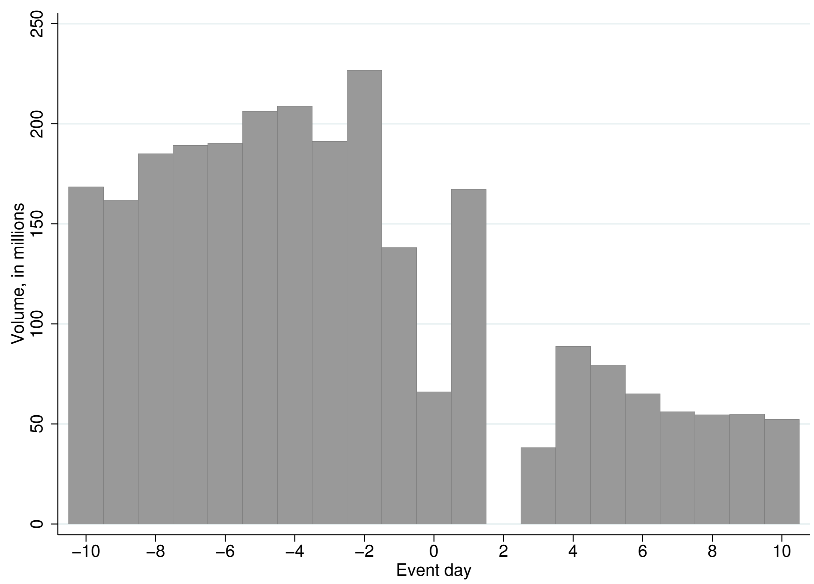
(d) Education

Figure 8: 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.



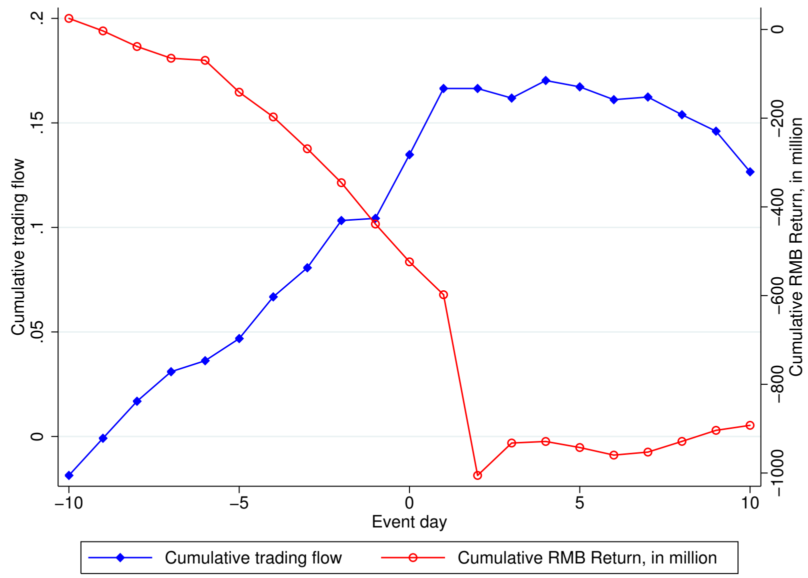
(a) All restructuring events



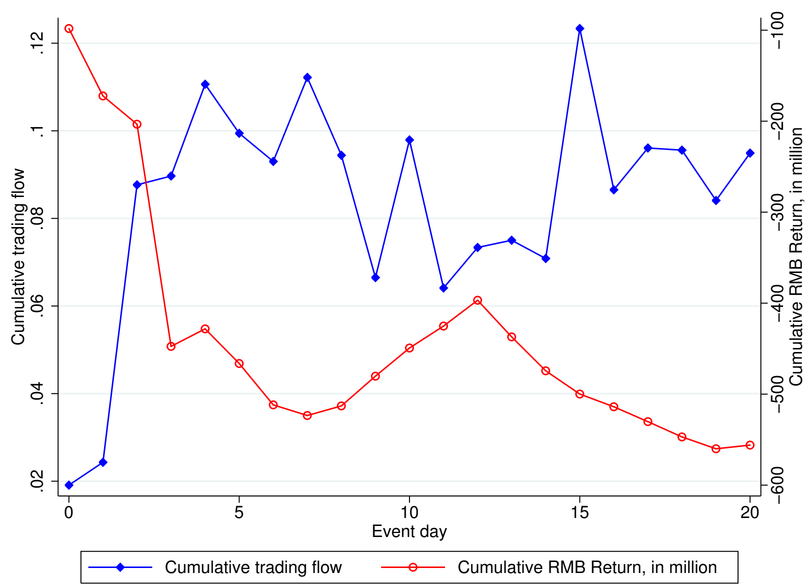
(b) Daily trading volume

Figure 9: B Funds during Restructuring Events

Note: Sub-figure 9a plots the evolution of NAV and B fund price during the 21-day window around the restructuring events. Sub-figure 9b plots the daily trading volume averaged across all restructuring events. Day 0 is defined as the first time that a B fund's closing price drops below the threshold.



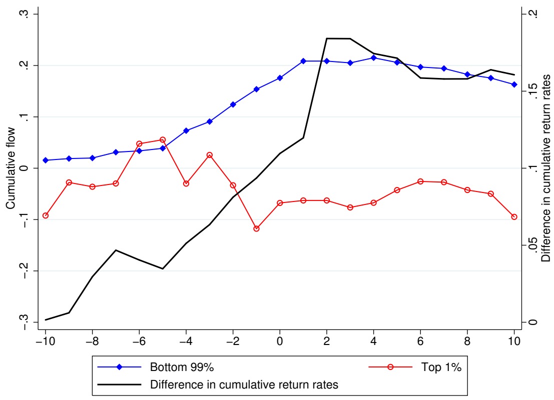
(a) All restructuring events (NAV < 0.25)



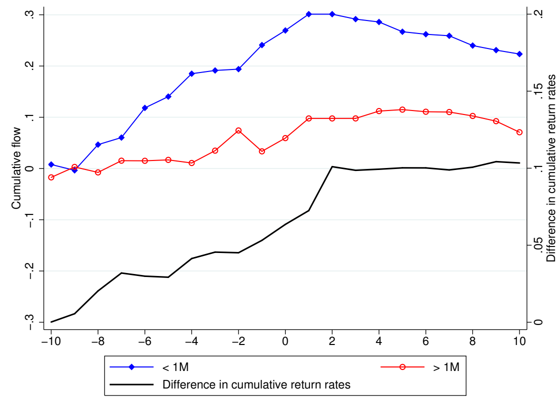
(b) NAV < 0.35

Figure 10: B Funds during Restructuring Events

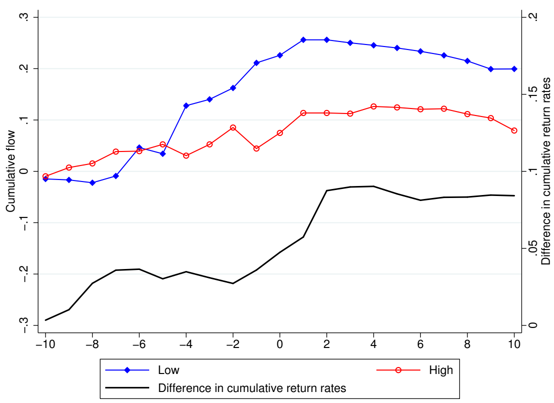
Note: Sub-figure 10a plots the distribution of trading flows around the restructuring events. Trading flow is normalized using the initial account balance. Sub-figure 10b plots the post-event trading flows and returns, where the event is defined by the first time a fund drops below 0.35.



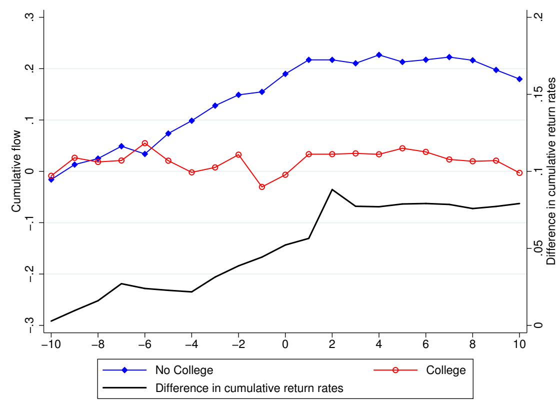
(a) Size



(b) Wealth



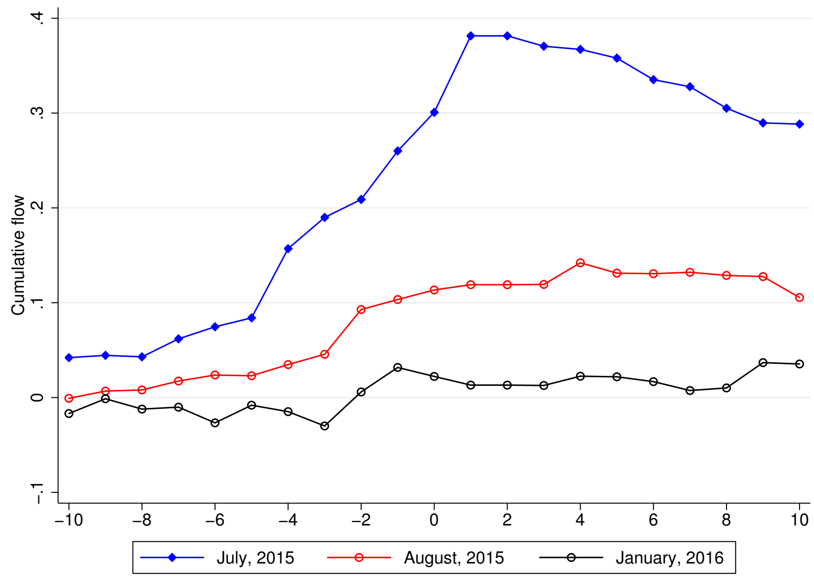
(c) Literacy



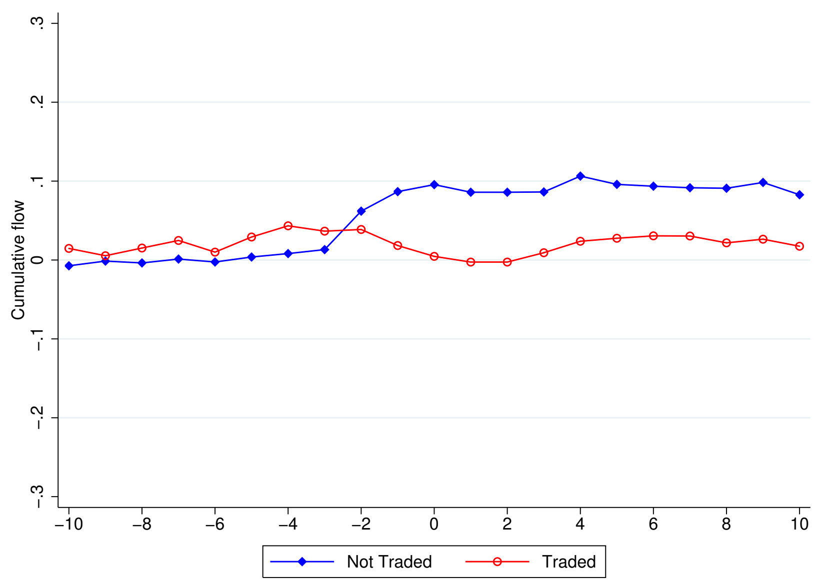
(d) Education

Figure 11: 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.



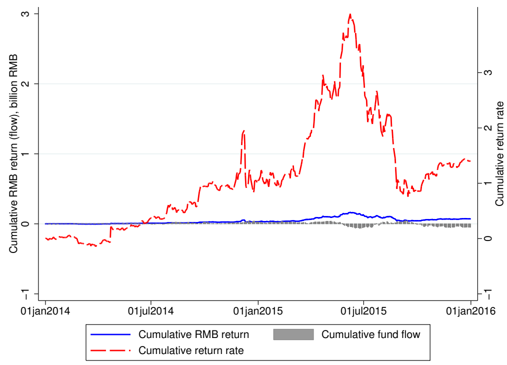
(a) Cumulative trading flow across waves



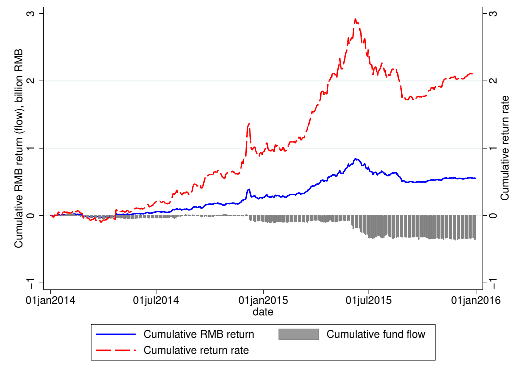
(b) Comparison between new and old investors

Figure 12: Evidence of Learning

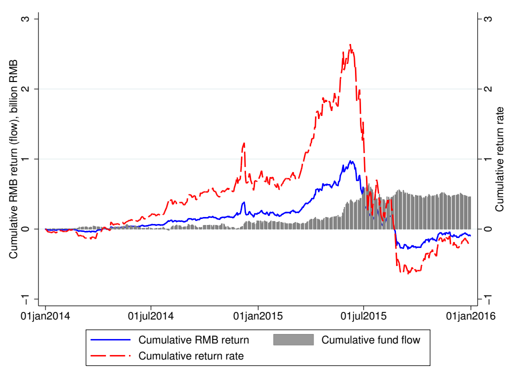
Note: Figure 12a plots the cumulative trading flow around restructuring events for three different waves: first in early July, second in late August, and third in early 2016. Trading flow is normalized using the initial account balance. Figure 12b compares the cumulative trading flow, during the latter 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.



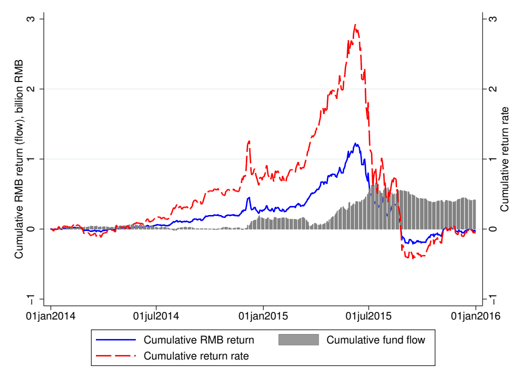
(a) Liquidity providers



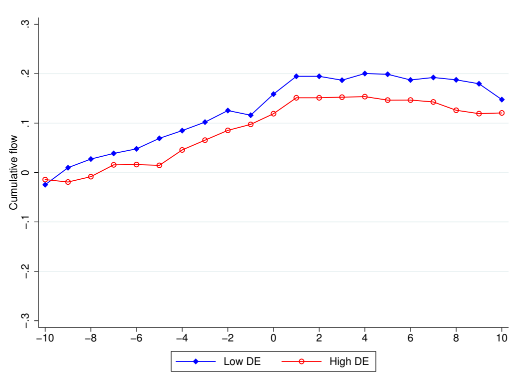
(b) Non-liquidity providers



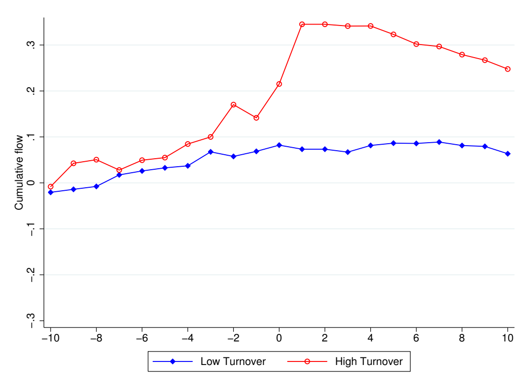
(c) High-disposition



(d) Low-disposition



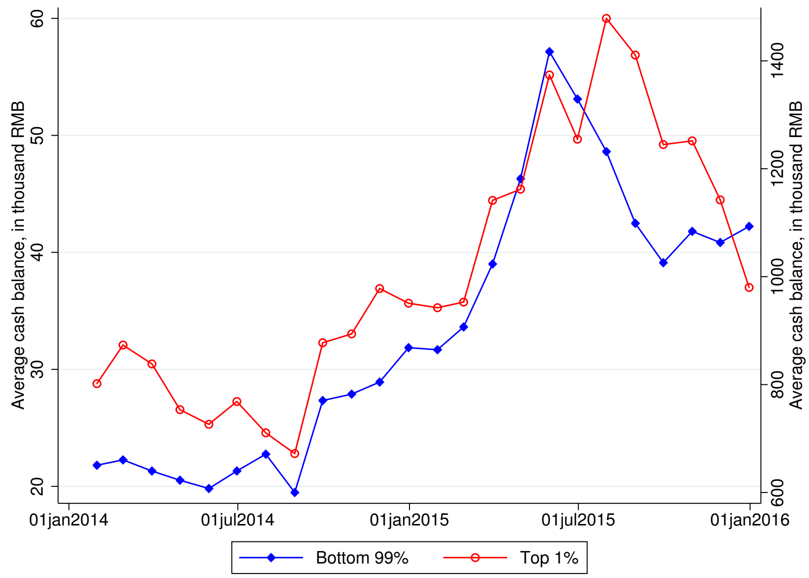
(e) Disposition effect



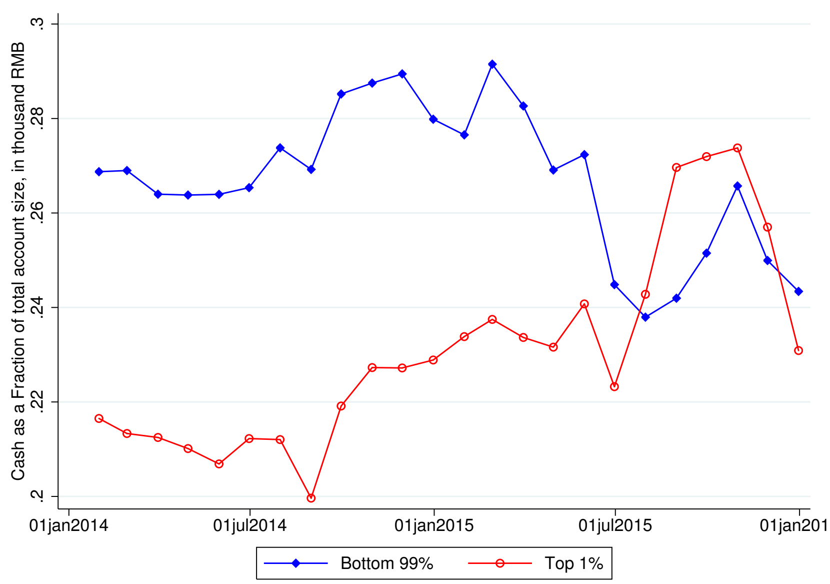
(f) Turnover

Figure 13: Evidence on Alternative Mechanisms

Note: Sub-figures 13a to 13d 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-figures13e and 13f 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.



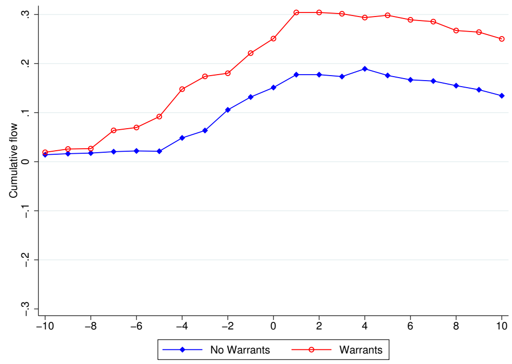
(a) Cash



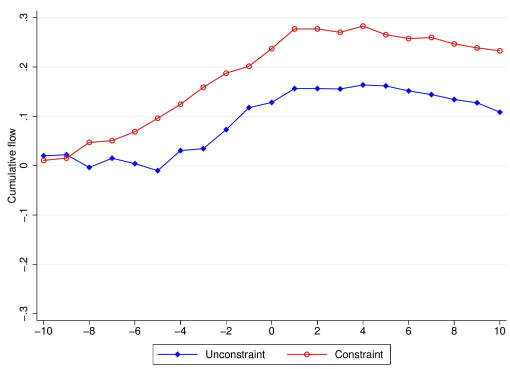
(b) Fraction of cash

Figure 14: Cash Holdings, 2014-2015

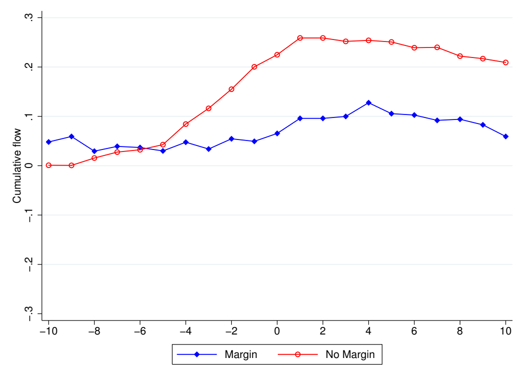
Note: Evolution of cash holdings for different investor groups. In Figure 14a, the left axis represents the bottom-99% investors and the right axis represents the top-1% investors. Cash represents the amount of cash balance in the account. Fraction of cash is calculated by dividing the amount of cash to the total account balance.



(a) Traded warrants before



(b) Cash positions



(c) Margin accounts

Figure 15: 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 constrained in borrowing if she has less than 10% of her account balance in cash.

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 market value of B funds by the total market 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*	0.011**	0.012**	0.010*	-0.005	-0.005
	(0.002)	(0.006)	(0.006)	(0.006)	(0.005)	(0.007)	(0.007)
Size (top 1%)	0.017***	0.029*	0.032**	0.034**	0.025**	-0.029*	-0.028*
	(0.006)	(0.016)	(0.016)	(0.016)	(0.012)	(0.015)	(0.015)
Financial literacy (good)	0.007***	0.023***	0.025***	0.025***	-0.011*	0.019***	0.020***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
College	0.005**	0.002	0.002	0.003	-0.001	0.006	0.006
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Female	0.008***	-0.043***	-0.044***	-0.044***	0.006	-0.001	-0.001
	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Experienced with B			-0.036***	-0.032***			-0.011
			(0.007)	(0.006)			(0.007)
ETF return				0.457***			
				(0.042)			
Constant	0.055***	-0.359***	-0.353***	-0.350***	0.104***	-0.127***	-0.124***
	(0.003)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)
Observations	20,181	17,206	17,206	17,206	3,716	3,002	3,002
R-squared	0.002	0.006	0.008	0.015	0.003	0.004	0.005

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 % $\times$ 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 difference 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

"Asset Complexity and the Return Gap"

A.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.

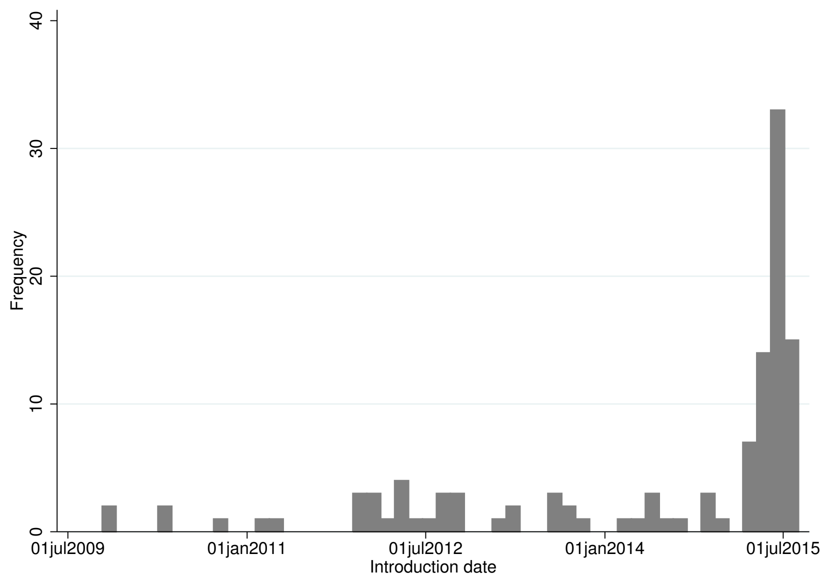


Figure A.1: Issuance of AB funds

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

A.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

A.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 fund price and B NAV to B NAV. B leverage is calculated as the ratio of A NAV to B NAV.

A.4 Additional Discussion of Limits to Arbitrage

As discussed in the paper, 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. 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 NAV, 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 NAV, 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.

In theory, there will be an arbitrage opportunity if the total market value of an A fund and

B fund exceeds the NAV 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 NAV 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 NAV, 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 NAV, 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.

A.5 Example of the Restructuring Process

Consider Penghua One-Belt-One-Road B Fund for a more concrete example. In Figure A.2a 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 Figure A.2b 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.

A.6 Returns for Investor Groups Sorted on Account Size

In Figure A.3, we sort investors into finer groups based on account size. Specifically, we sort them into four groups based on end-of-2013 maximum balance: top 1%, 91–99%, 81-90%, and below 80%. We find a monotonic pattern in both RMB returns and return rates from the less wealthy to the more wealthy group.

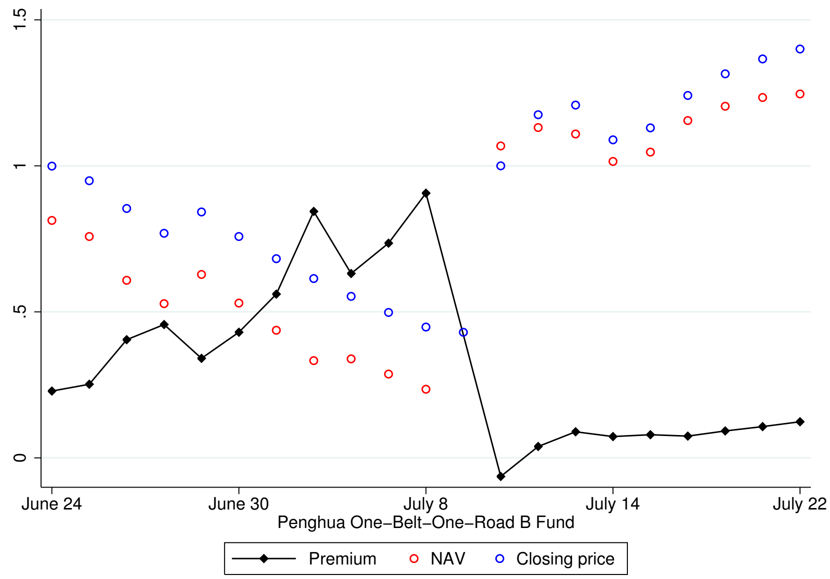
A.7 Alternative Measures of Return Rates for B Funds

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.

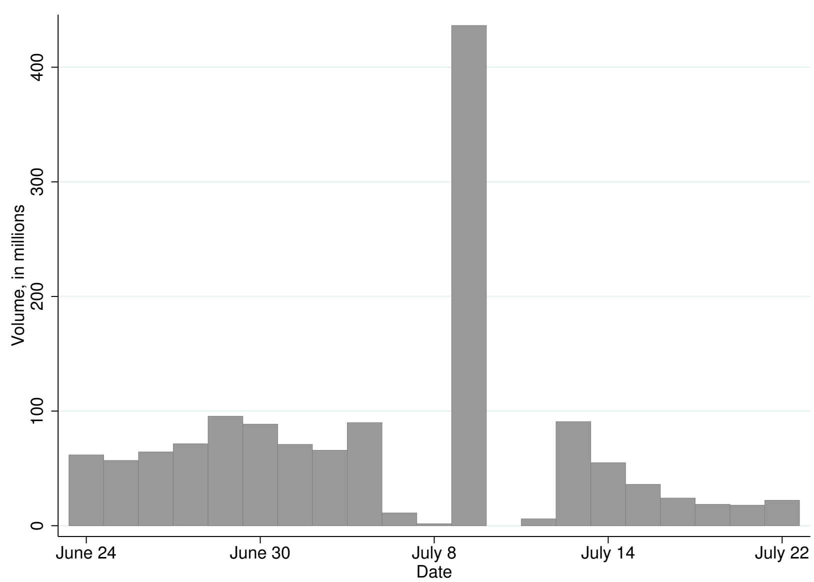
A.8 Additional results on the Trading of ETFs

A.8.1 Comparison of investor characteristics

Table A.4 compares investor characteristics across three investor groups: those who only traded AB funds, those who only traded ETFs, and those who traded both. Overall, we find that investors who traded AB funds are less wealthy and have a small account, are younger and less experienced with investing in the stock market, and have a lower financial literacy and are less well educated. Therefore, it appears that there is sorting between naivety and complexity: those who are drawn to the more complex assets are precisely the less sophisticated (and more vulnerable).



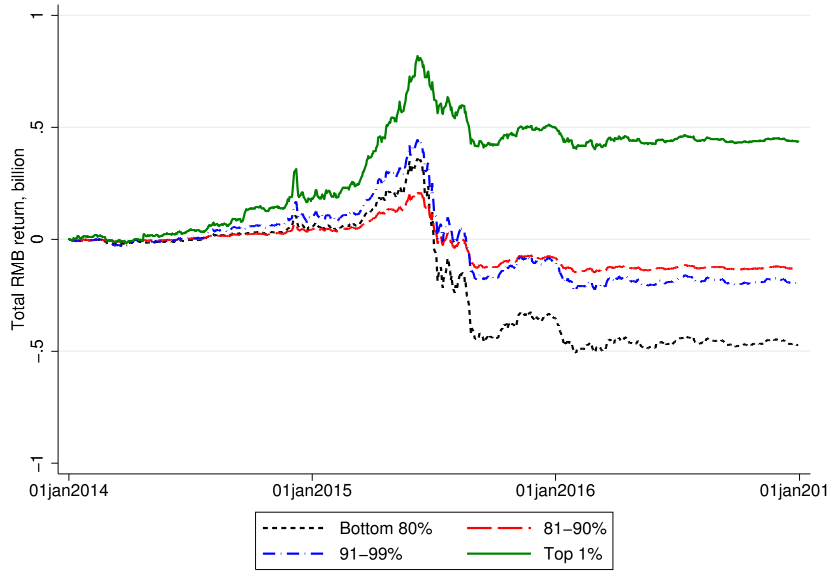
(a) Price and NAV



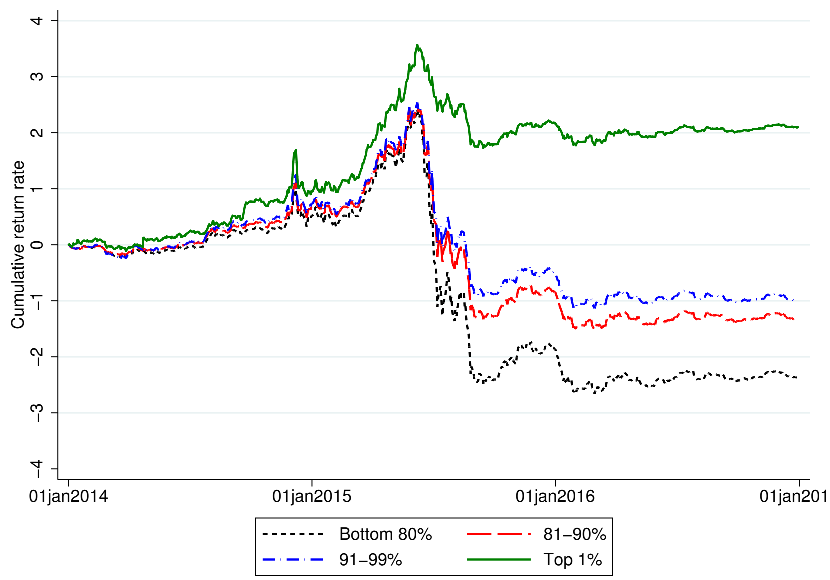
(b) Daily volume

Figure A.2: Restructuring Event of Penghua B Fund

Note: Sub-figure 9 plots the evolution of NAV and B fund price during the 21-day window around the restructuring event for Penghua One-Belt-One-Road Fund. Sub-figure A.2b plots the daily trading volume during the same period.



(a) RMB return



(b) Return rate

Figure A.3: 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, proxied by maximum account balance by the end of 2013. The 1%, 10%, and 20% cutoffs correspond to 5 million, 1 million, and 0.5 million RMB. Return rates are calculated by dividing total RMB return by average daily balance.

	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

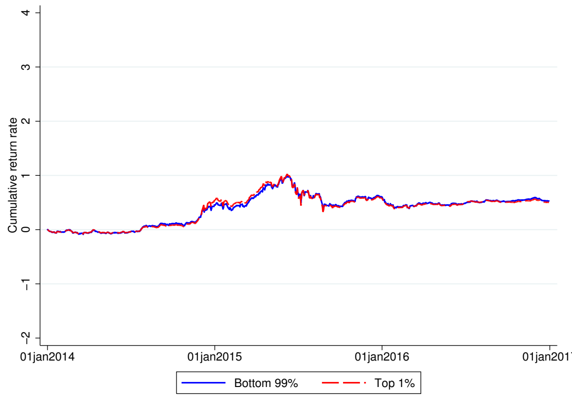
Table A.3: Regressing B Fund Returns on Demographic Variables

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.

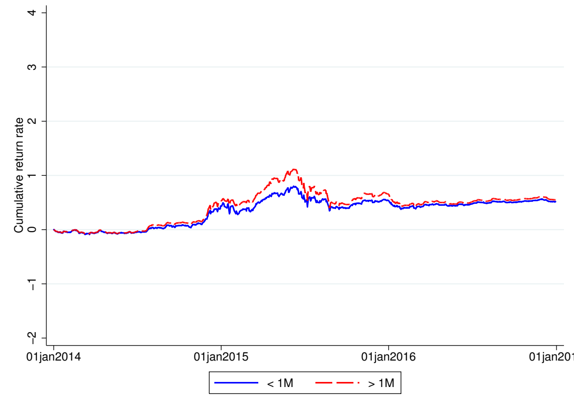
	N	Size (top 1%)	Wealth (>1M)	Years of experience	Financial literacy (good)	College	Age	Female
AB funds only	81,626	0.11	0.53	6.23	0.63	0.20	45	0.48
ETF only	9,235	0.29	0.59	7.49	0.66	0.23	48	0.51
Both	14,402	0.29	0.59	7.37	0.68	0.26	48	0.47

Table A.4: Comparison across investors who trade only AB funds, only ETFs, and both

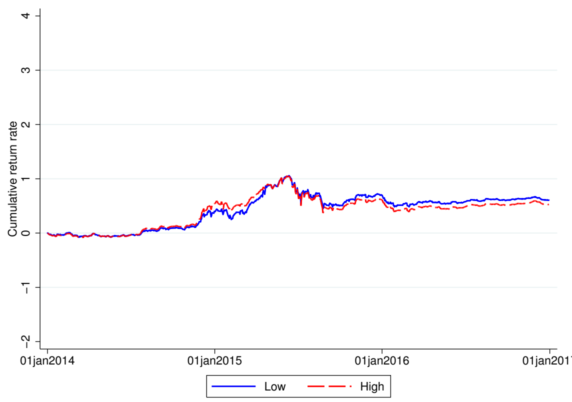
Note: Wealth (>1M) is an indicator function for self-reporting wealth greater than 1 million RMB. Size (1%) is an indicator function for having an account size in the top 1% of the distribution, which is around 5 million RMB. Financial literacy (good) is an indicator function for self-reporting good financial knowledge and practical skills. College is an indicator function for having a college degree or higher.



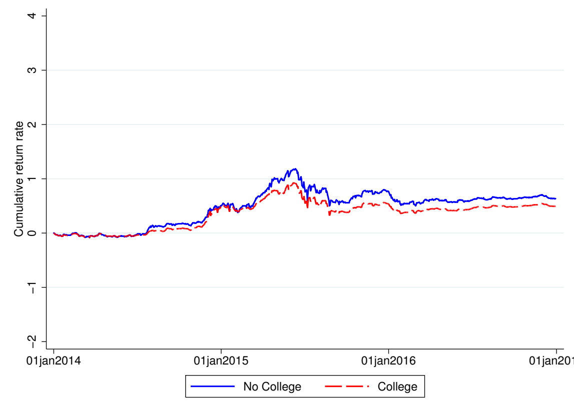
(a) Size



(b) Wealth



(c) Literacy



(d) Education

Figure A.4: ETF Return Rates for Investor Groups

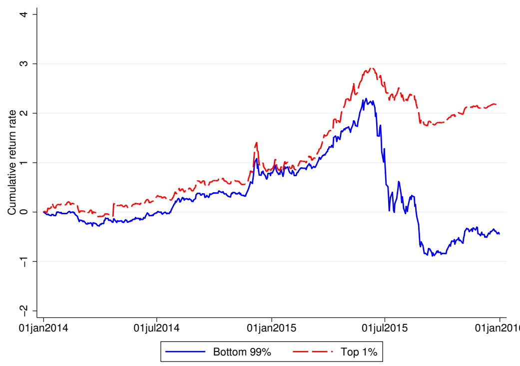
Note: Cumulative return rates from ETFs from 2014 to 2016 for investors of different demographic groups. Return rates are calculated by dividing RMB return by average daily balance. Top 1% investors have a maximum account balance greater than 5 million RMB by the end of 2013; bottom 99% investors have 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.8.2 Return rates for different investor groups

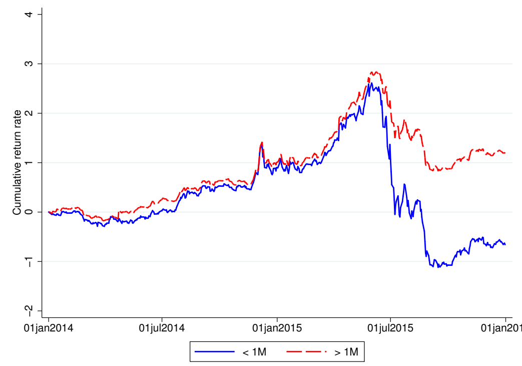
Table A.4 plots the return rates for different investor groups by controlling for their differences in total investment. In most cases, return rates are very similar across investor groups through both the run-up and the crash.

A.9 Returns for Funds with a Common Index

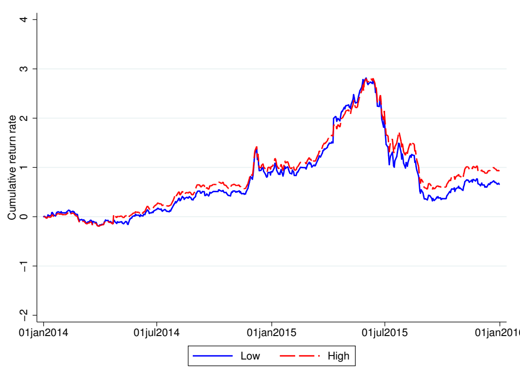
In Section 3, we study the returns for all B funds and all ETFs. In this section, we focus on the subset of B funds and ETFs that share an equity index. Figures A.5 and A.6 plot the return rates from 2014 to 2015. Results for RMB returns are similar to those in Section 3 and are available upon request. The patterns documented before are robust in these subsets of B funds and ETFs. In particular, the difference in return rate is much more pronounced for B fund returns.



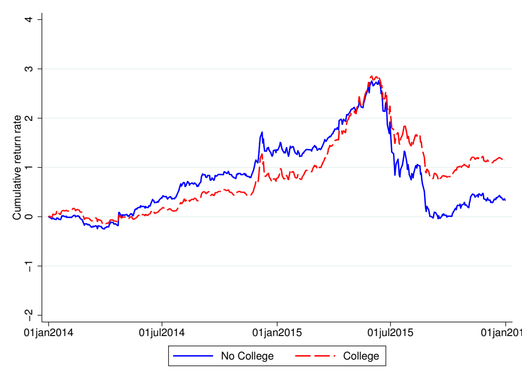
(a) Size



(b) Wealth



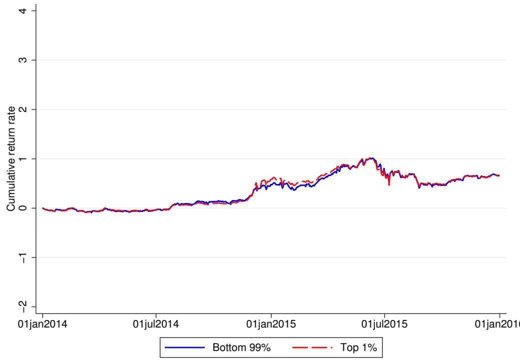
(c) Literacy



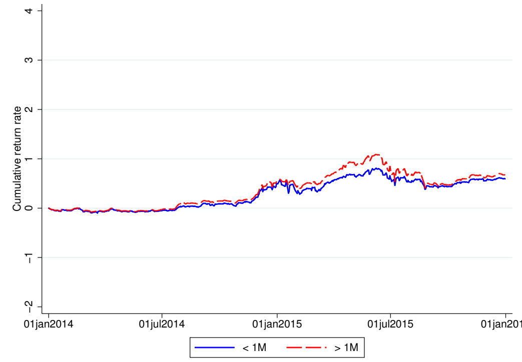
(d) Education

Figure A.5: B Return Rates for Investor Groups

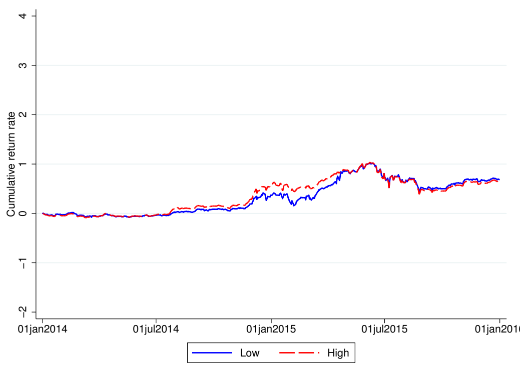
Note: Cumulative return rates from B funds from 2014 to 2015 for investors of different demographic groups. A B fund must have its underlying equity index shared with another ETF to be included in the analysis. Return rates are calculated by dividing RMB return by average daily balance. Top-1% investors 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.



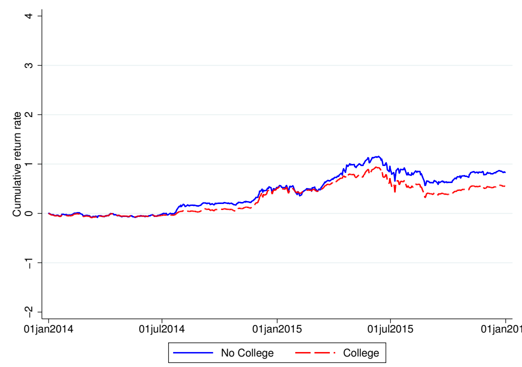
(a) Size



(b) Wealth



(c) Literacy



(d) Education

Figure A.6: 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.

A.10 Distribution of Restructuring Events

Figure A.7 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.7 shows, most of the restructuring events occurred during the 2015 Chinese market crash.

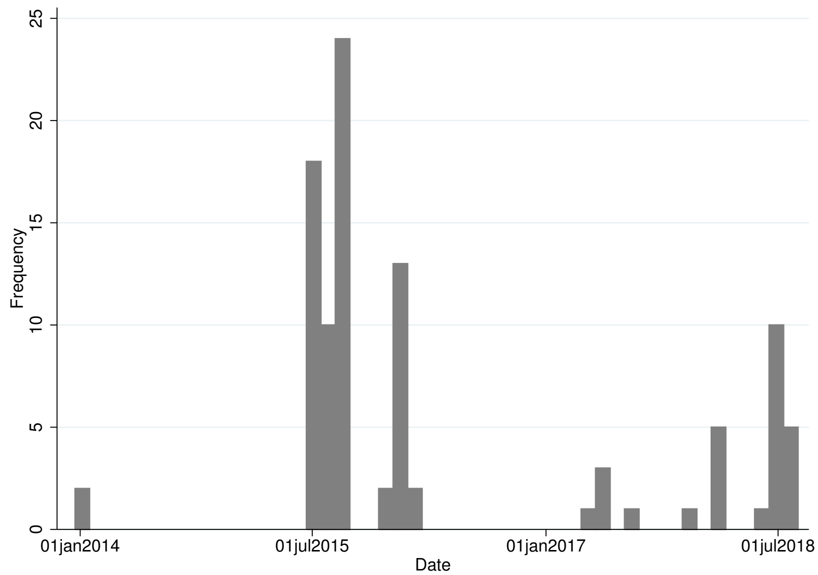


Figure A.7: Distribution of Restructuring Rvents

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.

A.11 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.8. 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%.

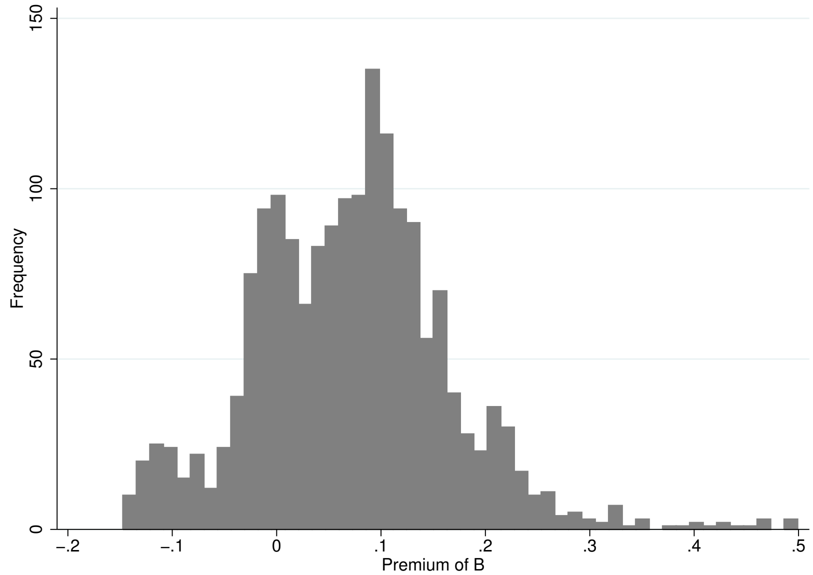


Figure A.8: Distribution of Premium

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.

A.12 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. In calculating these expected returns, we assume that once a restructuring event gets triggered, the associated premium will reset to zero post restructuring.

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.5: Expected returns prior to restructuring

A.13 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.6 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.6: Summary Statistics of Prospectuses

A.14 Additional results

A.14.1 Behavior of institutional investors

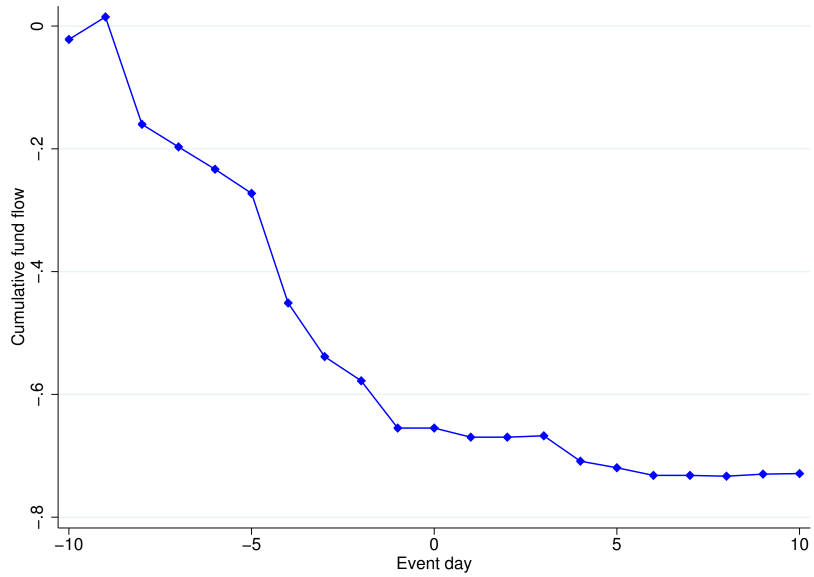
Due to data limitations, we only observe dozens of institutional investors, giving us only limited power to generalize their behavior during this episode.[33] However, even this small set may yield insights about the behavior of institutions. Figure A.9a plots their trading behavior during restructuring events and shows that institutional investors as a whole decreased their holdings by almost 70% prior to the restructuring events. Figure A.9b 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.

A.14.2 Behavior of A funds during the restructuring events

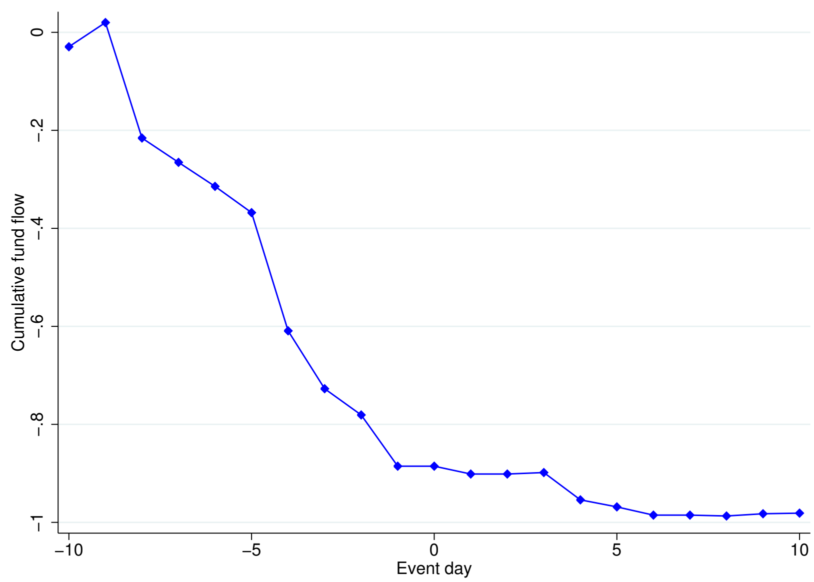
Most of our analysis so far has been devoted to B funds, because their leverage feature made them immensely popular during the 2015 Chinese stock market bubble. However, the behavior of A funds is also interesting: as "safe" assets, they were at one point trading at a 20% discount. We speculate, but do not show, that A funds traded at a discount due to arbitrage activity. Specifically, demand for B shares distorts B share prices such that A and B shares are overpriced relative to parent shares. This mispricing motivates arbitrageurs to create a parent fund at NAV, convert the parent into A and B shares, and sell the shares on the market. This puts downward pressure on A and B fund prices until no quasi-arbitrage opportunity exists.[34] If there isn't enough liquidity for A shares relative to B shares, this selling will depress the A fund price. 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.

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

[34] We call this a quasi-arbitrage because the trade takes time.



(a) All institutional investors



(b) “Active” institutional investors

Figure A.9: 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 A.9a considers all institutional investors. Sub-figure A.9b considers “active” institutional investors, who have traded at least 10 times in the sample.

A.15 Variable Definitions

Table A.7 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.7: Definitions of Investor Characteristics