Pricing Collateral: Evidence from Structured Funds *

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Abstract

Collateral value is central to asset pricing theory but difficult to measure empirically. We exploit the structure of Chinese funds that split identical cash flows into leveraged and unleveraged claims, allowing us to directly observe collateral value from tranche price wedges. We show that collateral value is positive and rises with leverage. Using exogenous variation, a one-standard-deviation increase in leverage raises collateral value by about 2%. Holding leverage fixed, greater investor disagreement increases collateral value, driven by borrower optimism about upside states rather than beliefs about downside risk. The disagreement type shapes asset prices and the shadow value of leverage.

Keywords: Collateral Value, Leverage, Collateral Constraint, Belief disagreement, Asymmetric disciplining

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1 Introduction

Many financial instruments embed leverage, including mortgage-backed securities (MBS) and asset-backed securities (ABS), which play a central role in financial markets and have been widely studied. Since the global financial crisis, economists and practitioners have recognized the importance of collateral and leverage. When assets can be pledged as collateral, their value reflects not only the discounted value of future cash flows but also the additional value arising from relaxed financing constraints.[1] This additional component, referred to as collateral value (Ai et al., 2020; Fostel & Geanakoplos, 2008; Geanakoplos, 2010b), can generate financial amplification, as borrowing constraints depend on, and in turn affect, asset prices (Kiyotaki & Moore, 1997; Krishnamurthy, 2003).

Despite its central role in macro-finance, empirical evidence on the existence and magnitude of collateral value remain limited. Identifying collateral value in the data faces three key challenges. First, leverage is difficult to measure directly. Second, isolating its pricing effect requires comparing the same asset with and without leverage, yet only one price is typically observed. Third, the forces that drive variation in leverage also affect asset prices, complicating causal identification. Beyond identification, collateral values depend on both leverage and the shadow value of leverage (Garleanu & Pedersen, 2011). Even when the collateral value can be identified, separating these components and understanding the determinants of the shadow value of leverage remain difficult (Lu & Qin, 2021).

"We overcome these challenges by exploiting a setting that makes collateral value directly observable: Chinese structured funds. Structured funds are closely related to the "primes and scores" in the U.S. market (Jarrow & O'Hara, 1989), as well as to securitized products such as ABS

1. We use "collateralizability" and "leverage" interchangeably in the rest of the paper. Highly collateralizable assets trade at high leverage.

and MBS (Gorton & Metrick, 2013). As illustrated in Figure 1, a structured fund consists of three components: a parent fund and two tranches, A and B. The structure decomposes the payoff of an open-end mutual fund (the parent fund) into two closed-end claims: a senior, interest-based A tranche (debt) and a junior, leveraged B tranche (equity). A-tranche investors receive a pre-specified return, while B-tranche investors receive the residual payoff. The parent fund delivers the unleveraged return on the underlying assets, whereas the B tranche provides leveraged exposure. Investors can hold any combination of these components.

[Insert Figure 1 About Here]

Three features make structured funds well suited for our analysis. First, fund net asset values (NAVs), market prices, and thus leverage are observed at a daily frequency.[2] Second, the parent fund and the A and B tranches share the same underlying asset pool, but only the A/B tranches embed leverage, allowing us to compare leveraged and unleveraged claims on identical cash flows. Third, there is substantial exogenous variation in leverage. With fixed promised payments to the A tranche, leverage varies with the value of underlying assets, which is largely exogenous to the relatively small structured fund market. In addition, contractual restructuring triggers generate discrete, exogenous changes in leverage. Together, these features provide a clean setting to identify collateral value and examine how it varies with leverage and belief disagreement.

These features imply sharp predictions for prices. In the absence of other frictions, the leveraged B tranche should trade above its fundamental value, while the debt-like A tranche should trade at its NAV; this is the classic result that for assets used as collateral, prices exceed fundamental value (Fostel & Geanakoplos, 2008). However, the paired conversion mechanism imposes a no-arbitrage condition that equates the combined market value of the A and B tranches with

2. The NAV reflects the fundamental value of the underlying assets, while the fund price is the secondary market trading price. Leverage based on prices is defined as parent NAV/(parent NAV – A-tranche market value), whereas NAV-based leverage replaces market value with A-tranche NAV.

the parent-fund NAV. Instead, it is reflected in relative pricing: the A tranche trades at a discount, while the B tranche trades at a premium. Given the small size of the structured fund market relative to the underlying asset market, this mechanism does not affect underlying asset prices and leaves the parent-fund NAV unchanged.

These tranche-level price wedges not only reveal collateral value, but also allow us to separate the role of leverage from the shadow value of leverage. The price wedges provide two equivalent measures of collateral value. The B tranche trades above its fundamental value due to embedded leverage, with its premium reflecting collateral value. The A tranche, in contrast, is implicitly issued by B-tranche investors to obtain leverage, and its discount captures the cost investors are willing to bear to access that leverage. Because these premia and discounts are directly observable, they provide a tractable basis for empirical identification of collateral value.

We uncover a clear and systematic pricing pattern in the data: the A tranche trades at a discount, while the B tranche trades at a premium. On average, the A fund trades at a 4.25% discount and the B fund at a 4.28% premium. These wedges are economically large, persistent over time, and robust across fund groups. We show that standard explanations, including the closed-end fund discount, cannot account for these patterns, providing direct evidence of positive collateral value.

At first glance, the persistent deviations of fund prices from their fundamental values, especially for the nearly risk-free A tranche, may appear puzzling. Why does a safe, debt-like claim trade at a discount? Two features of the setting resolve this puzzle. First, both the A-tranche discount and the B-tranche premium arise from collateral value: investors are willing to pay for access to leverage, which is embedded in the B tranche and financed through the A tranche. Second, although the parent fund can be transacted at NAV in the primary market, the A and B tranches cannot be purchased or redeemed separately and must be transacted as a bundle. This

limits arbitrage, allowing tranche-level price wedges to persist even when they appear large in isolation.

We next examine how collateral value varies with leverage. Using exogenous variation in leverage, we find that higher leverage increases collateral value: a one-standard-deviation increase in leverage raises collateral value by approximately 2.00%. To identify this effect, we use the parent fund NAV as an instrumental variable. The key identifying assumption is that structured fund investors are price takers in the underlying asset market, as structured funds account for only a negligible share of total market capitalization.[3] Fluctuations in underlying asset values therefore generate exogenous variation in parent fund NAV and, in turn, fund leverage. To further address potential endogeneity in actively managed funds, we restrict the sample to index funds and use the corresponding index level as an alternative instrument. The results remain robust.

To further establish causality, we exploit discrete changes in leverage induced by fund restructurings. Triggered when fund NAV crosses predetermined thresholds, these events generate sharp, plausibly exogenous shifts in leverage. Using a discontinuity-based difference-in-differences (DiD) design around these thresholds, we find that collateral value responds accordingly: restructured funds exhibit significant changes in collateral value relative to control funds. These results are robust to controls for fund riskiness, embedded option value, market liquidity, and daily price limits.

With both collateral value and leverage observable, we isolate the shadow value of leverage and examine how belief disagreement shapes collateral value (Garleanu & Pedersen, 2011; Simsek, 2013). We measure disagreement using two complementary approaches. First, we construct

3. Even at their peak, structured funds managed less than 500 billion RMB (81.79 billion USD), accounting for about five-thousandths of the total Chinese stock market capitalization. For a more precise comparison, we compute the market value of structured index funds relative to their benchmark indices; on average, this share is below one-thousandth.

a market-wide belief distribution using monthly surveys conducted under the supervision of the China Securities Regulatory Commission (CSRC). Second, we exploit differences in investor composition across tranches, where B tranches are primarily held by retail investors and A tranches by institutions, to infer group-specific beliefs. We extract retail beliefs from textual analysis of posts on an online investor forum and institutional beliefs from financial news coverage.

We find that disagreement increases the shadow value of leverage: holding leverage fixed, greater belief dispersion is associated with significantly higher collateral value per unit of leverage (Miller, 1977). Moreover, the nature of disagreement is central. Collateral value increases strongly when borrowers are more optimistic about upside states, but is largely unresponsive to optimism about downside states. This asymmetric response is exactly the pattern predicted by Simsek (2013), where disagreement about upside states drives the demand for leverage and generates asymmetric price discipline across states.

Related Literature This paper provides direct empirical evidence on the asset-pricing implications of collateral value and its interaction with heterogeneous beliefs. The link between collateralizability and asset prices has been extensively studied in theoretical work (Fostel & Geanakoplos, 2012; Garleanu & Pedersen, 2011; Geanakoplos, 2010a; Gorton, 2009).[4] While these models differ in structure, they share a common prediction: collateralizability raises asset prices by relaxing funding constraints.

Empirical evidence on this topic remains limited. Using experimental methods, laboratory studies such as Cipriani et al. (2018) and Cipriani et al. (2021) show that leveraged assets command higher prices than otherwise identical unleveraged assets. Establishing similar effects in

4. Gong and Phelan (2020) and Gong and Phelan (2022) show that asset prices rise when they can be collateralized or tranched, and that variation in collateralizability leads to variation in prices. Other important contributions include Brunnermeier (2009), Adrian and Shin (2010), Acharya and Viswanathan (2011), and Chabakauri and Han (2020), all of which highlight how leverage raises asset prices.

real-world data is substantially more challenging, as leverage is endogenously determined and counterfactual prices are not observed. Existing empirical studies typically rely on one-time policy shocks affecting specific assets (Fang et al., 2020; Chen et al., 2023), which provide valuable identification but do not capture time-series variation in the shadow value of leverage. As emphasized by Lu and Qin (2021), collateral value reflects both leverage and its shadow value, and disentangling these components remains difficult in most settings.

Our setting addresses these challenges by providing rich time-series and cross-sectional variation in leverage within a unified framework. This allows us to directly measure collateral value and separately identify the roles of leverage and its shadow value.[5]

By isolating the shadow value of leverage and examining its determinants, we also connect to the literature on collateral value and heterogeneous beliefs. A large literature shows that belief disagreement affects asset prices, typically by pushing them upward (Diether et al., 2002; Harrison & Kreps, 1978; Miller, 1977). Simsek (2013) emphasizes that not only the level but also the nature of disagreement matters: disagreement about upside states has a stronger effect on prices than disagreement about downside states. Our setting allows us to test this mechanism directly. Consistent with this prediction, we show that both the level and the nature of belief disagreement shape collateral value, with effects driven by disagreement about upside states. This provides direct empirical support for the mechanism in Simsek (2013).

The remainder of the paper is organized as follows. Section 2 provides the institutional background of Chinese structured funds. Section 3 introduces the conceptual framework and develops the testable hypotheses. Section 4 describes the data, summary statistics, and variable

5. Gao et al. (2022) and Qiu et al. (2022) also study Chinese structured funds. Qiu et al. (2022) examine the liquidity implications of deleveraging, while Gao et al. (2022) study how asset complexity amplifies return differences across investors, taking fund premia as given. In contrast, our paper explains the origin of these premia. More broadly, the structured fund setting provides a rare opportunity to test theories of collateralizability in real-world data, similar in spirit to studies of Chinese warrant markets (Xiong and Yu, 2011; Pearson et al., 2021).

construction. Section 5 presents the empirical results, including the identification of collateral value and its relation to leverage and belief disagreement. Section 6 concludes.

2 The Structured Funds in China

This section describes the institutional setting of Chinese structured funds and highlights the features that make them well suited for our analysis. We begin by outlining the basic structure of these funds and their payoff decomposition. We then discuss the key institutional features (paired conversion, time-varying leverage, and restructuring rules) that generate observable price wedges and exogenous variation in leverage. Together, these features provide the foundation for identifying collateral value and its determinants in the empirical analysis.

2.1 Overview of the Structured Funds

A typical structured fund in China consists of three funds: the parent fund (P), the A fund, and the B fund. The payoff of the parent fund is split into two tranches. First, the debt-like A fund offers a predetermined return, typically between 5%-7%.[6] Second, the leveraged B fund receives the residual payoff after the A tranche is paid. B-fund investors effectively borrow from A-fund investors and obtain the leveraged return of the parent fund. In securitization terms, the A fund resembles a senior tranche, while the B fund corresponds to the equity tranche and is repaid only after the A tranche is fully satisfied.

Panel A of Table 1 summarizes the institutional features of the parent, A, and B funds. The

6. In comparison, the interest rate charged for margin trading is 8% - 9%, implying relatively inexpensive leverage within structured funds. Moreover, individual investors must meet eligibility requirements to access margin trading, including maintaining an average account balance above RMB 500,000 for the preceding 20 trading days and having at least six months of trading history. Structured funds, in contrast, imposed no additional eligibility requirements prior to September 2016. Table B5 in Internet Appendix B provides further details on A-fund interest rates.

A-fund NAV accrues at the promised rate of return, while the B-fund NAV equals the residual value of the parent-fund NAV after payments to the A tranche. The combined payoff of the A and B funds therefore equals that of the parent fund. Most A and B funds are exchange-traded closed-end funds that are ineligible for stand-alone primary market redemption or subscription. Their market prices may deviate from NAV, and this deviation is captured by the fund premium. In contrast, parent funds are typically non-tradable open-end funds that can be redeemed or purchased at NAV, which reflects the value of the underlying assets.[7] Daily prices and NAVs are reported by exchanges and fund companies and are publicly available.

[Insert Table 1 About Here]

Panel B of Table 1 reports fund-level summary statistics. Among the 217 funds, 148 are equity funds, 67 are bond funds, and 2 are hybrid funds.[8] Approximately two-thirds of the funds are index funds. Figure 2 further reports investor composition across tranches and underlying asset types. Institutional ownership of the parent fund is comparable to that of non-structured funds, but ownership differs markedly across tranches: B funds are predominantly held by retail investors, whereas A funds are largely institutionally held. These patterns likely reflect differences in embedded leverage and associated risk exposure across tranches.

[Insert Figure 2 About Here]

[Insert Figure 3 About Here]

7. Sixteen structured funds listed on the Shanghai Stock Exchange have exchange-traded parent funds. However, most structured funds are listed on the Shenzhen Stock Exchange, where parent funds are non-tradable.
8. We collect data on all structured funds issued before August 2015. As new structured fund offerings were prohibited thereafter, our sample covers nearly the entire universe of Chinese structured funds. Equity (bond) funds invest at least 80% of assets in equities (bonds), while hybrid funds allocate substantial shares to both asset classes.

Figure 3 shows the number of new structured fund issuances and their total assets under management. After a slow start, issuance surged during the 2014–2015 stock market boom, peaking in June 2015. The rapid expansion was likely driven by the attractiveness of B funds, which offered low-cost embedded leverage with minimal entry barriers. However, the July 2015 market crash abruptly halted this growth, as B-fund investors experienced amplified losses due to leverage, and no new structured funds were approved after August 2015. Subsequent regulatory tightening further curtailed the market: new rules introduced in late 2016 raised investor eligibility requirements, substantially reducing the qualified investor base and weakening liquidity.[9] Finally, China's 2018 asset management reform explicitly prohibited tranche structures in publicly offered products, effectively marking the end of structured funds.

2.2 Features of the Structured Funds

2.2.1 The Paired Conversion

Structured funds feature a paired conversion mechanism that allows shares to be converted between the parent fund and the A and B tranches without changing NAV (see the dashed lines in Figure 1).[10] The share ratio of the A and B funds, $s_A : s_B$, is fixed and determines the fund's initial leverage.[11] Investors may combine s_A shares of the A fund and s_B shares of the B fund into $s_A + s_B$ shares of the parent fund and redeem at NAV, or split parent-fund shares into A and B shares and sell them in the secondary market. As the combined A and B funds have the same NAV as the

9. The draft of the regulation (in Chinese): http://finance.ce.cn/rolling/201609/10/t20160910_15784651.shtml; The final version of the regulation (in Chinese): http://www.gov.cn/xinwen/2016-11/26/content_5137977.htm

10. Some structured funds do not offer paired conversion (see Table 1). These funds differ from typical structured funds in several aspects: they often lack a separate parent fund, and their A funds are open-end rather than exchange-traded closed-end funds. We exclude such funds from the subsequent analysis.

11. For equity funds, the typical A–B ratio is 1:1, while for bond funds it is 7:3. Because all tranches are issued at par, the allocation ratio pins down initial leverage. For example, a 1:1 ratio implies that B-fund investors borrow 1 to purchase assets worth 2, yielding leverage of 2. Regulatory limits cap initial leverage at 2 for equity funds and 10/3 for bond funds. See Table 2 for the average initial leverage.

parent fund, such a conversion design seems natural.

[Insert Figure 4 About Here]

The paired conversion mechanism creates an arbitrage link between the parent fund NAV and the combined market prices of the A and B tranches. If the total price of the A and B funds falls below the parent fund NAV, investors can purchase both tranches, convert them into parent-fund shares, and redeem at NAV; the reverse strategy applies when the combined price exceeds NAV. Although the conversion process takes approximately two days, this mechanism ties tranche prices closely to the parent fund NAV. The design resembles the prime and score structures introduced in the United States in the 1980s. However, Jarrow and O'Hara (1989) show that in that setting price discrepancies persisted, reflecting market imperfections. In contrast, Figure 4 shows that the pricing disparity in structured funds remains economically small, with an average deviation of 0.048%, suggesting that the paired conversion mechanism is generally effective in aligning tranche prices with the parent fund NAV.

2.2.2 Continuous and Exogenous Variation in Leverage

Another distinctive feature of Chinese structured funds is that, unlike fixed-leverage products such as leveraged ETFs in the United States and Europe, their leverage fluctuates continuously with the parent-fund NAV.[12] Fund leverage is defined as the asset-to-equity ratio,

$$Leverage \equiv \frac{(s_A + s_B)NAV_P}{s_B p_B} = \frac{(s_A + s_B)NAV_P}{(s_A + s_B)NAV_P - s_A p_A}$$

where NAV_P is the parent-fund NAV per share, p_A and p_B are tranche prices, and s_A and s_B denote share allocations. The first equality follows from the definition of leverage, and the second from the paired conversion condition equating the combined A and B prices with the parent-fund NAV.

12. Frazzini and Pedersen (2022) investigate the asset pricing implications of embedded leverage in options and leveraged ETFs, which offer fixed leverage.

Because the structured fund market is small relative to the underlying asset market, underlying asset values, and thus the parent-fund NAV, are effectively exogenous. Fluctuations in NAV_P therefore generate high-frequency, exogenous variation in fund leverage.

2.2.3 Fund Restructurings

Because fund leverage fluctuates continuously, structured funds include restructuring clauses that keep leverage within a prescribed range (approximately 1–5) by imposing discrete leverage adjustments. These clauses, specified in fund prospectuses, protect A-fund investors and preserve the economic viability of the structure. We briefly summarize the mechanism here and provide a detailed illustration in Internet Appendix D.

Ascending and descending restructurings reset NAV-based leverage to its initial level.[13] Ascending restructuring is triggered when the parent-fund NAV exceeds a threshold (typically 1.50), which corresponds to low leverage; descending restructuring is triggered when the B-fund NAV falls below a threshold (typically 0.25), corresponding to high leverage. In both cases, tranche shares are reallocated to restore leverage to its initial level, ensuring that the B-fund NAV remains positive and the A tranche remains protected. If a trigger condition is met on day -1, the end-of-day NAV on the following trading day (day 0) serves as the computation base, and restructuring is completed on day 1.

Between 2011 and 2017, there were 65 ascending and 105 descending events (See Figure B1 for more details). Ascending restructurings were concentrated during the 2015 market boom, whereas descending restructurings clustered around the subsequent crash. On average, leverage increases by 33% in ascending restructurings and declines by 60% in descending restructurings.

13. NAV leverage is defined as $(s_A + s_B)NAV_P/(s_B NAV_B)$ and measures leverage using fundamental values rather than market prices. Structured funds also feature regular (annual or semi-annual) restructurings that result in only minor leverage adjustments.

3 Hypothesis Development

A structured fund splits the payoff of a parent fund into two tranches: a debt-like A tranche and a leveraged B tranche. This setting allows us to directly observe collateral value and its cross-sectional and time-series variation, thereby providing a natural laboratory to test collateral-based asset pricing theories. As emphasized by Geanakoplos (2003), an asset's price can be decomposed into its fundamental value and its collateral value. In the absence of other frictions, if collateral value exists and is positive, the leveraged B tranche should trade above its fundamental value, with the price wedge reflecting collateral value:

$$p_B > NAV_B \tag{1}$$

Because the A tranche resembles risk-free debt with a promised payoff, it should trade at its fundamental value:

$$p_A = NAV_A \tag{2}$$

However, the paired conversion mechanism imposes a no-arbitrage constraint linking tranche prices with the parent fund NAV. For expositional clarity, consider funds with a 1:1 share allocation ratio. The following condition must hold:

$$p_A + p_B = 2NAV_P = NAV_A + NAV_B \tag{3}$$

The first equality follows from the paired conversion, which equates the combined market value of the A and B tranches to the parent-fund NAV, and the second follows from the tranche design. Equations 1, 2, and 3 cannot hold simultaneously. Therefore, if the B tranche trades above its fundamental value due to collateral value, the A tranche must trade at a discount.

Economically, leveraged investors obtain exposure by implicitly issuing the A tranche at a below-fundamental price. The A-fund discount thus reflects a *willingness to pay* for leverage. Consistent with Fostel and Geanakoplos (2008) and Geanakoplos and Zame (2014), who interpret collateral value as the liquidity value of the contract issued, the A-tranche discount captures the liquidity cost investors are willing to incur in order to lever up.

We interpret the price wedge on the B tranche as the market manifestation of investors' valuation of levered exposure in an environment with constrained leverage opportunities. Equivalently, this wedge captures the willingness to pay for leverage when access to leverage requires issuing the A tranche at a discount. Formally, we define collateral value as:

$$\begin{aligned} CV_A &:= -w_A = -\frac{p_A - NAV_A}{NAV_A} \\ CV_B &:= w'_B = \frac{w_B}{NAVLev - 1} = \frac{p_B - NAV_B}{NAV_B}\frac{1}{NAVLev - 1} \\ CV_A &= CV_B \end{aligned} \tag{4}$$

where w_A and w_B denote the percentage price wedges of the A and B tranches, respectively, and $NAVLev$ denotes NAV-based leverage. The B-tranche wedge is rescaled by $NAVLev - 1$ to measure the pricing deviation per unit of borrowed capital, i.e., per RMB value of the A tranche.[14] Based on this reasoning, we state our first hypothesis:

Hypothesis 1 *If collateral value is positive, the A-tranche price wedge w_A must be negative, and the B-tranche price wedge w'_B must be positive.*

The tranche price wedges reflect collateral value, which in turn depends on two components: leverage and the shadow value of leverage (Garleanu & Pedersen, 2011; Lu & Qin, 2021). We next

14. To see this, note that $CV_A := (NAV_A - p_A)/NAV_A = (p_B - NAV_B)/NAV_B \times (NAV_B/NAV_A) = w_B NAV_B/NAV_A$. Because $NAV_B/NAV_A = 1/[(NAV_A + NAV_B)/NAV_B - 1] = 1/(NAVLev - 1)$, we obtain $CV_A = w_B/(NAVLev - 1) = w'_B = CV_B$.

examine how these two forces jointly determine collateral value. First, collateral value is predicted to increase with leverage (Fostel & Geanakoplos, 2012; Geanakoplos, 2010b). Intuitively, higher leverage amplifies the value of the borrowing capacity embedded in the contract. Consistent with Geanakoplos (2003), we therefore posit:

Hypothesis 2 *Collateral value increases with leverage. As leverage rises, the absolute values of A- and B- fund price wedges (CV_A, CV_B) increase.*

We next turn to the shadow value of leverage. Given empirical estimates of collateral value and leverage, we isolate the shadow component by scaling collateral value by effective leverage. We define the corresponding "unlevered" shadow value as

$$UnitCV_A := \frac{CV_A}{Leverage - 1},\ UnitCV_B := \frac{CV_B}{Leverage - 1},\ UnitCV_A = UnitCV_B \tag{5}$$

This measure captures the shadow value of leverage per unit of effective leverage, abstracting from the mechanical amplification induced by leverage itself. Under the theoretical decomposition in Garleanu and Pedersen (2011), where collateral value scales proportionally with leverage, this rescaling recovers the marginal shadow value of relaxing the borrowing constraint.

The shadow value of leverage should vary with market conditions, particularly with investors' belief distributions, which shape the demand for leveraged exposure. Drawing on the heterogeneous-belief literature, we derive two predictions. First, the shadow value of leverage should increase with the level of belief disagreement (Miller, 1977), since disagreement raises the valuation gap between optimistic borrowers and pessimistic lenders. Second, following Simsek (2013), the nature of disagreement also matters. The shadow value of leverage should be higher when borrower optimism is concentrated on the upside, i.e., when borrowers assign a higher probability to favorable states. In contrast, when optimism reflects a lower perceived likelihood

of downside states, its effect on the shadow value of leverage should be limited.

Hypothesis 3 *The shadow value of leverage increases with the level of belief disagreement. Moreover, it responds asymmetrically to the nature of disagreement: it rises when borrowers assign a higher probability to favorable (upside) states relative to lenders, but is less responsive when disagreement primarily reflects a lower perceived likelihood of unfavorable (downside) states.*

Taken together, these hypotheses generate clear empirical implications. The first hypothesis states that the tranche price wedges provide direct evidence of collateral value, which can be decomposed into leverage and the shadow value of leverage. Based on this decomposition, the remaining two hypotheses examine how collateral value varies with leverage and belief disagreement. In the following sections, we test these predictions using the unique institutional features of structured funds.

4 Data and Variable Construction

We empirically test the three hypotheses using structured fund data and investor belief disagreement measures constructed from survey and textual sources. The following subsections introduce the data sources, variable definitions, and summary statistics for the structured fund and belief datasets in turn.

4.1 Structured Fund Data

Structured fund data are obtained from the China Stock Market & Accounting Research Database (CSMAR), which provides basic fund characteristics and daily NAVs, prices, premia, and leverage. We further collect institutional details from fund prospectuses, including the presence

of a parent fund, the paired conversion mechanism, and whether the parent, A, and B tranches are exchange-traded.

Our sample includes structured funds that satisfy three criteria: an open-end parent fund, closed-end A and B tranches, and the presence of a paired conversion mechanism. We exclude observations with missing price or NAV data. The sample runs from January 2011 to June 2016. We begin in 2011, when the structured fund market began to expand rapidly. The regulatory draft released on September 9, 2016 significantly tightened investor eligibility requirements and led to substantial changes in the market. To avoid contamination from this regulatory shift, we end the sample in June 2016. The final sample comprises 145 structured funds, including 136 equity funds, 7 bond funds, and 2 hybrid funds. Among them, 131 are index funds.

[Insert Table 2 About Here]

Panel A of Table 2 reports summary statistics for the structured funds; detailed variable definitions are provided in the Appendix. The average fund leverage is 2.104. For the parent fund, we report the pricing error, *PceError* (%), defined as the percentage deviation between the market value of the A and B tranches and the parent-fund NAV implied by the conversion ratio. Specifically, for a fund with an initial A–B share allocation ratio of $s_A : s_B$, *PceError* is defined as $(\frac{s_A}{s_A+s_B}p_A + \frac{s_B}{s_A+s_B}p_B - NAV_P)/NAV_P$. Panel A shows an average pricing error of 0.048%, indicating that the paired conversion mechanism is generally effective in aligning the combined market value of the A and B tranches with the parent-fund NAV. Among the 131 index funds, the average tracking error is -0.014%, suggesting that these funds closely track their benchmark indices.

We report the daily NAV, price, and premium (%) for the parent, A, and B tranches. The premium corresponds to the price wedge defined in Section 3, that is, the percentage deviation

between price and NAV. The A-tranche premium is defined as $(p - NAV)/NAV$, capturing the deviation of price from its fundamental value. The B-tranche premium is defined analogously but is further rescaled by NAV-based leverage minus one, so that it measures the price wedge per unit of borrowed capital. As shown in Panel A, both the mean and median A-tranche premia are negative, whereas those of the B tranche are positive. This pattern provides preliminary evidence consistent with Hypothesis 1, which we examine formally in Section 5.1.

4.2 Belief Disagreement Data

In addition to the structured fund data, data for belief disagreement is also required in testing the hypotheses related to the shadow value of leverage. Unlike structured fund data, which are directly generated by financial markets, belief disagreement is inherently unobservable and must be inferred from external sources.

We construct belief disagreement measures using two complementary data sources. First, we use belief distributions from market-wide surveys conducted by official authorities. Second, leveraging recent advances in textual analysis, we extract investor beliefs from large-scale textual data. The survey-based measure provides a representative aggregate belief distribution but does not capture heterogeneity across different types of investors. In contrast, the text-based approach yields indirect belief measures yet allows us to estimate disagreement across distinct investor groups. The following subsections describe these two data sources in detail.

4.2.1 Survey-based Belief Disagreement

Investor surveys provide direct evidence on expectations about future market performance. Since 2011, the China Securities Investor Protection Fund Corporation, under the supervision of the China Securities Regulatory Commission (CSRC), has conducted monthly surveys on in-

vestors' expectations of stock market returns. The survey asks respondents to indicate their anticipated change in the Shanghai Composite Index over the next month, choosing among three categories: increase ("up"), remain unchanged ("neutral"), or decrease ("down").[15] The monthly survey reports the proportion of respondents selecting each category, thereby yielding a distribution of investor beliefs about future market performance. The composition of the respondents is usually 90% retails and 10% institutions, so that this survey mostly reflects the view of retails, i.e., the borrowers.

Panel B of Table 2 reports the proportions of investors expecting the market to rise, remain unchanged, or decline, denoted by $Prob^{Up}$, $Prob^{Neut}$, and $Prob^{Down}$, respectively. The means of these three probabilities are comparable, each close to 30%. However, $Prob^{Up}$ and $Prob^{Down}$ exhibit substantially greater dispersion, as evidenced by the differences between their 5th and 95th percentiles. Together, these variables characterize the representative belief distribution, which we use to construct measures of belief disagreement.

Hypothesis 3 requires proxies for both the level and the nature of belief disagreement. To capture the level of disagreement, we construct two measures of belief dispersion based on the survey belief shares:

$$\begin{aligned} Dispersion &= 1 - \sum_{k \in \{Up, Neut, Down\}} (Prob^k)^2 \\ Entropy &= - \sum_{k \in \{Up, Neut, Down\}} Prob^k log(Prob^k) \end{aligned} \tag{6}$$

Larger values of *Dispersion* and *Entropy* indicate a higher level of dispersion in the belief distribution.

Measuring the nature of belief disagreement requires a belief distribution with more than

15. Respondents may also select "uncertain"; however, this category accounts for approximately 10% of responses and does not convey directional information relevant to our analysis. We therefore exclude it and rescale the remaining three response shares so that they sum to one. Results remain robust without this rescaling. The survey also elicits expectations over three- and six-month horizons; our results are robust to using these longer-term measures.

two states, which the survey data provide. As emphasized by Simsek (2013), optimism may arise either from assigning a higher probability to favorable (upside) states or from assigning a lower probability to unfavorable (downside) states. These distinct forms of optimism can have different implications for collateral value. To capture this distinction, we construct a measure that reflects the relative importance of upside optimism conditional on downside optimism. Upside optimism corresponds to the probability assigned to favorable ("up") states, measured by $Prob^{Up}$. Downside optimism, in contrast, reflects a lower perceived likelihood of unfavorable ("down") states and is captured by $1 - Prob^{Down}$. We therefore proxy the nature of belief disagreement as:

$$RelaUp = Prob^{Up}/(1 - Prob^{Down}) \tag{7}$$

A caveat is that, strictly speaking, identifying the nature of belief disagreement requires observing belief distributions for both borrowers and lenders simultaneously and comparing their cross-sectional differences. In contrast, the survey-based measure reflects a market-wide representative belief distribution. As a result, $RelaUp$ primarily captures time-series variation in aggregate optimism rather than cross-sectional disagreement about which states investors disagree on. To obtain more refined measures of asymmetric disagreement, we therefore turn to text-based analysis, which allows us to estimate heterogeneous belief distributions across investor groups.

4.2.2 Text-based Belief Disagreement

Advances in textual analysis and the increasing availability of large-scale textual data facilitate the estimation of belief measures from text (Dim, 2025). Importantly, text from different sources allows us to proxy beliefs for distinct investor groups, enabling the identification of cross-sectional disagreement regarding which states investors disagree on. As shown in Figure

2, B tranches are predominantly held by retail investors, whereas A tranches are largely institutionally owned. Exploiting this institutional feature, we collect text data representative of retail investors and institutions to construct group-specific belief measures.

To proxy retail investors' beliefs, we use posts from the Chinese social media platform Guba East Money, where retail investors actively exchange views on individual stocks. Prior studies show that posts on Guba East Money reflect retail investor sentiment and contain valuable information for stock pricing and corporate governance (Ang et al., 2021; Huang et al., 2024). We obtain the Guba data from the China Research Data Services (CNRDS) platform. For each stock on each trading day, posts are classified into three categories: positive, neutral, and negative. We compute the share of posts in each category and aggregate these stock-day measures to the fund-day level as follows:

$$Prob^{k}_Borrower_{fd} = \sum_{i} \omega_{ifd} PostShare^{k}_{id} \tag{8}$$

where i, f, d represent stock, fund, and trading day, respectively. We restrict the analysis to structured funds that track stock indices and obtain the list of constituent stocks and their corresponding index weights ω_{ifd}. $PostShare^{k}_{id}$ denotes the fraction of posts related to stock i on day d that are classified as positive, neutral, or negative, with $k \in \{Up, Neut, Down\}$.[16] For each fund, we obtain the fund-day level belief as the weighted average of beliefs on the constituent stocks, with the weight being the index value weight ω_{ifd}. Thus, $Prob^{k}_Borrower_{fd}$ represents the weighted-average belief of retail investors regarding the likelihood that fund f will move up, remain unchanged, or decline on day d, with weights given by the index composition.

To proxy institutional beliefs, we rely on online financial news.[17] The text of online financial

16. Weighting posts solely by their count may ignore differences in influence. We therefore conduct additional robustness tests using alternative weights based on the number of comments or reads. See appendix

17. This choice is motivated by three considerations. First, financial news is produced by professional journalists

news is obtained from the China Research Data Services (CNRDS) platform. Each news article is linked to specific stocks and classified into positive, neutral, and negative categories based on textual sentiment. For each stock on each trading day, we compute the share of news in each sentiment category and aggregate these stock-day measures to the fund-day level as follows:

$$Prob^{k}_Lender_{fd} = \sum_{i} \omega_{ifd} NewsShare^{k}_{id} \tag{9}$$

where the notation follows equation 8. $NewsShare^{k}_{id}$ represents the fraction of news related to stock i on trading day d that is classified as positive, neutral, or negative. $Prob^{k}_Lender_{fd}$ thus captures institutions' perceived likelihood that fund f will move up, remain unchanged, or decline on day d, where $k \in \{Up, Neut, Down\}$. For stock-day observations with no financial news coverage, the corresponding weight is set to zero, and the remaining weights are rescaled to sum to one.[18]

Before presenting the summary statistics, we discuss potential distortions in the text-based belief measures. First, retail beliefs may be distorted due to selective sharing. Individuals are more likely to communicate and share information following gains than losses (Kaustia & Knüpfer, 2012). As a result, downside probabilities may be understated. Second, institutional beliefs inferred from financial news may also be distorted. News reports typically convey directional sentiment about firm or market prospects (Tetlock, 2007), making purely neutral statements less

who aggregate views from institutions, and thus reflects institutional perspectives. Second, we avoid using analysts reports because analysts tend to avoid negative opinions due to conflicts of interest and career concerns (Hong & Kubik, 2003; Kolasinski & Kothari, 2008). This concern is particularly relevant in the Chinese market, where analysts rarely issue sell recommendations. We discuss potential selective reporting in online news later in this subsection. Third, we focus on online news rather than print media because online sources are updated more frequently and are subject to relatively less editorial delay. Our results remain robust when using print media instead.

18. A potential concern is that stock-day observations without financial news may still have social media posts, leading to differences in coverage between retail and institutional belief measures. As a robustness check, we impose common coverage across social media and financial news sources; the results remain robust (see Appendix Table X).

common in news coverage. In addition, negative news may also be underreported due to reputational concerns, regulatory pressure, or conflicts of interest.

We acknowledge the presence of such distortions, particularly for institutional beliefs, where incentives to avoid reporting adverse information may be economically meaningful. Nevertheless, three considerations mitigate these concerns. First, if both retail and institutional beliefs are downward-biased with respect to negative states, such distortions may partially offset when we focus on cross-group differences. Second, our empirical design is less sensitive to distortions that are persistent and market-wide, as these would be non-selective across funds and over time. Finally, despite their limitations, text-based measures provide the most direct and scalable approach to estimating heterogeneous beliefs across investor groups.

Panel C of Table 2 presents summary statistics for the text-based belief measures. First, the text-implied borrower beliefs exhibit broad similarity to the survey-based beliefs. Given that approximately 90% of survey respondents are retail investors, this similarity provides support for the validity of the text-based approach. Notably, however, the text-implied downside probability is lower than that implied by the survey, consistent with the selective-sharing concern discussed above.

Second, comparing post-based (retail) and news-based (institutional) beliefs, the news-based measures assign a higher probability to upside states. This pattern is somewhat counterintuitive, as institutions, who are lenders in our setting, might be expected to hold more conservative views. One possible explanation is the more prominent selective and directional reporting in financial news. Importantly, our identification relies on time-series variation in the differences between retail and institutional beliefs, rather than on their absolute levels. To the extent that any distortion is persistent and not systematically correlated with fund-level characteristics, it is unlikely to materially affect our analysis.

Using the text-based belief measures, we construct the following proxies for belief disagreement. First, to capture the level of disagreement, we measure the distance between borrower and lender belief distributions using the total variation distance:

$$DTV = \frac{1}{2} \sum_{k \in \{Up, Neut, Down\}} |Prob^k_Borrower - Prob^k_Lender| \tag{10}$$

A larger DTV indicates greater divergence between borrower and lender beliefs.

Second, to capture the nature of disagreement, we separately measure disagreement related to upside and downside states:

$$RelaUp_Text = \frac{Prob^{Up}_Borrower}{Prob^{Up}_Lender},\ RelaDown_Text = \frac{Prob^{Down}_Lender}{Prob^{Down}_Borrower} \tag{11}$$

$RelaUp_Text$ captures upside-oriented disagreement, measuring the extent to which borrowers assign a higher probability to favorable (upside) states relative to lenders. A larger value indicates stronger upside optimism among borrowers. Similarly, $RelaDown_Text$ captures downside-oriented disagreement. Because downside optimism corresponds to a lower perceived likelihood of unfavorable states, we construct $RelaDown_Text$ as the ratio of lenders' downside probability to that of borrowers, so that a larger value reflects stronger downside optimism among borrowers. To mitigate potential distortions in text-implied beliefs and facilitate comparison across specifications, we standardize $RelaUp_Text$ and $RelaDown_Text$ to have mean zero and unit standard deviation.

5 Empirical Findings

Exploiting the detailed structured fund data and belief measures, this section empirically tests the three hypotheses. The following subsections examine the existence and magnitude of collateral value, the relationship between leverage and collateral value, and how belief disagreement affects the shadow value of leverage, respectively.

5.1 The Magnitude of Collateral Value

Hypothesis 1 predicts that if collateral value is positive, the A-tranche price wedge (premium) should be negative, whereas the B-tranche premium should be positive. Because fund premia are directly observable, this prediction can be tested empirically. Figure 5 presents the daily average premia for the A and B tranches, together with their 95% confidence intervals. For each trading day, we compute the cross-sectional average premia across all structured funds. The A- and B-tranche premia lie symmetrically on opposite sides of the horizontal axis. Consistent with Hypothesis 1, the B-tranche premium is significantly positive for most of the sample period, while the A-tranche premium is negative.

[Insert Figure 5 About Here]

[Insert Table 3 About Here]

Table 3 further reports the average collateral value inferred from the A and B tranches, denoted by $Cola_A$ and $Cola_B$, respectively, for the full sample and across different fund groups. Following Equation 4, the collateral value inferred from the A tranche equals the negative of the A-tranche premium, whereas that inferred from the B tranche equals the rescaled B-tranche premium. Consistent with the patterns shown in Figure 5, both $Cola_A$ and $Cola_B$ are significantly positive.

We next examine collateral value across different fund groups. First, collateral value remains positive for funds investing in different asset classes. Equity, bond, and hybrid funds all exhibit significantly positive collateral value. Notably, the average collateral value is largest for bond funds, followed by equity funds and then hybrid funds. This pattern may reflect differences in leverage, as the average leverage for equity, bond, and hybrid funds is 2.05, 3.03, and 1.57, respectively. We explore this channel further in Section 5.2, where we formally test the relationship between leverage and collateral value.

Second, collateral value is also positive for both index and non-index funds, although it is substantially smaller for the latter. This difference cannot be explained by leverage, as the average leverage for index and non-index funds is 2.08 and 2.38, respectively. Instead, the difference likely reflects variation in market conditions. Non-index funds are concentrated in the early part of the sample period, when belief disagreement was less pronounced. We examine the role of belief disagreement in Section 5.3.

A potential concern is that, because both the A and B tranches are closed-end funds, the well-documented closed-end fund discount may also contribute to the observed nonzero fund premia (Berk & Stanton, 2007; Chopra et al., 1993; Lee et al., 1991). However, several considerations suggest that the patterns we document cannot be explained solely by the closed-end fund discount. First, the closed-end fund discount cannot reconcile the opposite signs of the A- and B-tranche premia. Second, for a more direct comparison, we focus on non-structured closed-end funds that track the same indices as the structured funds, thereby controlling for differences in underlying assets. These non-structured funds exhibit an average discount of -0.013%, which remains substantially smaller than the premia or discounts observed for structured funds. Third, the closed-end fund discount cannot account for the systematic variation in fund premia with leverage and belief disagreement, as we demonstrate in the following subsections.

Overall, our empirical evidence supports Hypothesis 1 and confirms the presence of positive collateral value.

5.2 Leverage and Collateral Value

Having established the existence of positive collateral value, this subsection examines how collateral value varies with leverage, following the predictions of Geanakoplos (2003). We first conduct instrumental variables (IV) analysis on the full sample to establish causality, and then provide additional evidence using a difference-in-differences approach around restructuring events. Finally, we present robustness checks to rule out potential confounding factors.

5.2.1 Instrumental Variable (IV) Analysis

Higher leverage amplifies the value of the borrowing capacity embedded in the contract, implying higher collateral value. In the structured fund setting, leverage varies with the parent fund NAV, which is plausibly exogenous because the structured fund market is too small to affect the pricing of the underlying assets. We therefore use the parent fund NAV as an IV for fund leverage.

[Insert Table 4 About Here]

Column (1) of Table 4 reports the first-stage results. With fund-level debt fixed, leverage declines as asset value increases. In the structured fund setting, the promised repayments of A tranches are fixed, so leverage decreases as the value of the underlying assets (proxied by the parent fund NAV) rises. Controlling for structured fund pricing error *PceError*, as well as fund and trading-day fixed effects, column (1) shows a significant negative relationship between parent fund NAV and fund leverage, supporting the relevance of the instrument. We further

report Kleibergen–Paap underidentification and weak-instrument tests to confirm that the IV specification does not suffer from weak instruments or underidentification.

Columns (2) and (3) report the two-stage least squares (2SLS) estimates for the effect of leverage on collateral value, using the parent fund NAV as the instrumental variable. The two columns use collateral value inferred from the A- and B-tranche premia, respectively. Controlling for structured fund pricing error *PceError*, as well as fund and trading-day fixed effects, the results indicate that higher leverage leads to significantly greater collateral value. A one-standard-deviation increase in leverage raises collateral value by 1.96%–2.06%, corresponding to 27.2%–31.6% of a standard deviation of collateral value.

The key identification assumption is that the structured fund market is small relative to the market for the underlying assets, so that variation in the parent fund NAV is exogenous to structured fund investors. Nevertheless, one may be concerned that, for actively managed funds, asset allocation may respond to fund inflows and outflows, potentially linking parent fund NAV to the trading behavior of structured fund investors. To address this concern, columns (4)–(6) restrict the sample to index funds and use the underlying index level as the instrumental variable for leverage. The results remain robust in both statistical significance and economic magnitude.

Overall, the empirical results support Hypothesis 2, indicating that higher leverage leads to significantly greater collateral value.

5.2.2 Difference-in-Differences(DiD) Analysis

In addition to the continuous variation in leverage used in the IV analysis, fund restructurings generate sharp exogenous changes in leverage. These events are triggered when NAVs cross preset thresholds, allowing us to conduct additional identification tests using a discontinuity-based difference-in-differences (DiD) approach.

For illustration, Figure 6 shows leverage and premium changes within a [-5,5] trading-day window around restructuring events. Restructuring allocations are determined by the end-of-day NAV on day 0 and implemented on day 1. Relative leverage is measured as actual leverage scaled by its level on day -5, while premium changes are calculated relative to the premium on day -5.

[Insert Figure 6 About Here]

Figure 6 plots the median premium changes and relative leverage for ascending and descending restructurings.[19] In the 60 ascending restructurings in our sample, leverage increases by about 33.6%. The A-tranche premium declines by 4.0%, while the B-tranche premium rises by roughly 4.4%. In contrast, the 94 descending restructurings reduce leverage by 63.5% on average. Consistent with the predicted decline in collateral value, the A-tranche premium rises by about 4.66%, while the B-tranche premium falls by 7.5%.[20]

The event study suggests that fund premia move sharply with leverage. However, restructurings are typically triggered when fund values reach extreme levels, raising the concern that the observed premium changes may reflect extreme market conditions rather than leverage adjustments. Moreover, because restructuring rules are known in advance, investors may front-run these events. To address these concerns, we implement a discontinuity-based DiD analysis exploiting the pre-specified restructuring thresholds.

Ascending restructurings occur when the parent fund NAV exceeds 1.5. For each restructuring event, we identify control funds that experience no restructuring within the [-5,5] window and whose parent fund NAV on the triggering day (day -1) lies just below the 1.5 threshold. We

19. Medians are used to mitigate the influence of extreme values. Average changes are reported in Figure B3 of Internet Appendix B.

20. For ascending restructurings, the B-tranche premium begins to rise on day -1, suggesting that some investors may anticipate the restructuring and front-run it (Gao et al., 2022). For descending restructurings, pre-event leverage increases steadily because the restructuring is triggered by a low B-tranche NAV, making leverage highly sensitive to NAV changes. In addition, many descending restructurings occur during the sharp market decline in 2015Q3.

then estimate a DiD specification using observations within the [-5,5] window. $Treat$ equals one for restructured funds and zero for control funds, while $Post$ indicates post-restructuring observations. The interaction term $Treat \times Post$ captures the effect of restructuring on leverage and fund premia. Descending restructurings are triggered when the B-tranche NAV falls below 0.25. For each event, we select control funds with no restructuring in the [-5,5] window and triggering-day B-tranche NAVs just above the threshold.

[Insert Table 5 About Here]

Panels A and B of Table 5 report the results for ascending and descending restructurings, respectively. Consistent with earlier findings, ascending (descending) restructurings lead to sharp increases (decreases) in leverage, accompanied by corresponding increases (decreases) in collateral value. These discontinuity-based DiD results provide further support for Hypothesis 2.

5.2.3 Further Discussions

We conduct several robustness checks to address potential frictions. We briefly summarize them below, with detailed descriptions provided in Internet Appendix B. First, our theoretical framework assumes a risk-free debt tranche, but risk in the A tranche may also generate negative premia. To address this concern, we control for fund risk, the aggressiveness of debt promises, and their interaction terms. The results remain robust. Second, fund premia may reflect embedded option values. We discuss potential sources of such options and show that they cannot account for our findings. Third, premia may arise from the liquidity services provided by the funds. We address this concern by comparing premia and market liquidity between structured and non-structured funds tracking the same index. The results also remain robust when controlling for fund liquidity. Finally, because closed-end funds are subject to daily price limits, we examine

whether price limits affect fund premia. Excluding the potential impact of price limits does not alter our results.

5.3 Belief Disagreement and Collateral Value

Collateral value depends on both leverage and the shadow value of leverage. Having established the role of leverage, this subsection examines the shadow value of leverage. To isolate this component, we focus on collateral value per unit of effective leverage and study how the level and nature of belief disagreement affect it. The following subsections present evidence based on survey-based and text-based beliefs, respectively.

5.3.1 Evidence from Survey-based Beliefs

We first examine how belief disagreement affects the shadow value of leverage using belief distributions inferred from a market-wide survey. Conducted monthly under the supervision of the CSRC, the survey provides a representative distribution of investors' expectations about market performance over the following month. Measures of the level and nature of belief disagreement are constructed from this distribution.

Table 6 reports the results on how belief disagreement affects collateral value. The dependent variable is collateral value per unit of leverage, which excludes the mechanical effect of leverage and proxies for the shadow value of leverage. The main independent variables are *Dispersion* and *Entropy*, both capturing the extent of belief disagreement. All specifications control for structured fund pricing error *PceError* and include fund fixed effects. Consistent with Hypothesis 3, greater belief disagreement is associated with a significantly higher shadow value of leverage. A one-standard-deviation increase in *Dispersion* (*Entropy*) raises collateral value per unit of leverage by about 1.8% (1.2%), corresponding to roughly 45% (30%) of its standard deviation. These

findings are consistent with the heterogeneous-belief literature, suggesting that disagreement among investors raises asset prices.

[Insert Table 6 About Here]

Moreover, the nature of belief disagreement also matters, indicating that what investors disagree about has important implications for asset pricing. Table 7 examines how upside beliefs, downside beliefs, and relative upside optimism affect collateral value per unit of leverage. First, collateral value per unit of leverage is significantly higher when more investors are optimistic about the upside, that is, when they expect the market to rise. Second, downside optimism has an insignificant impact on collateral value, as shown in columns (2) and (4), suggesting that asset prices change little when investors assign a lower probability to adverse states. Finally, to assess the relative importance of upside versus downside optimism, columns (3) and (6) use $RelaUp$ as the key independent variable. The results show that, holding downside optimism constant, collateral value is significantly higher when optimism concentrates on the upside.

[Insert Table 7 About Here]

In summary, using the representative belief distribution inferred from monthly investor surveys, we show that both the level and the nature of belief disagreement matter for collateral value. Collateral value increases with the degree of disagreement and rises further when investors assign a higher probability to the upside state. In contrast, optimism about the downside has an insignificant impact on collateral value. These findings are consistent with Hypothesis 3.

However, this analysis primarily exploits time-series variation in the representative belief distribution. Belief disagreement also arises from cross-sectional differences across investor groups, which we examine in the next subsection.

5.3.2 Evidence from Text-based Beliefs

To obtain belief distributions across different investor groups, we rely on beliefs inferred from textual data. Borrower (retail) beliefs are inferred from posts on Guba, while lender (institutional) beliefs are extracted from online financial news. These text-based measures allow us to estimate belief disagreement across investor groups.

Table 8 examines how cross-sectional belief disagreement affects collateral value. *DTV* measures the distance between the belief distributions of borrowers and lenders. All specifications control for structured fund pricing error *PceError* and include fund and trading-day fixed effects. The results show that greater distance between borrower and lender beliefs is associated with significantly higher collateral value per unit of leverage. This effect remains robust after controlling for average market optimism, as shown in columns (2) and (4). These findings provide further support for Hypothesis 3.

[Insert Table 8 About Here]

Table 9 further examines how the nature of belief disagreement affects collateral value. The dependent variables in Panels A and B are collateral value per unit of leverage inferred from the A and B tranches, respectively. Column (1) conducts a test similar to Table 7, examining how borrowers' beliefs about the upside and downside affect collateral value. Consistent with earlier results, upside optimism significantly increases collateral value, while downside optimism is insignificantly related to it. Column (2) additionally includes lender beliefs, and the results indicate that only borrower upside optimism matters. This is intuitive: borrowers implicitly issue risk-free debt and therefore capture only the upside of asset returns, implying that they are willing to pay higher prices only when they perceive the upside to be more valuable.

[Insert Table 9 About Here]

Columns (3) and (4) directly examine the impact of relative optimism on collateral value. $RelaUp$ measures the extent to which borrowers are more optimistic about the upside relative to lenders. Consistent with Hypothesis 3, greater upside optimism is associated with significantly higher collateral value. In contrast, *RelaDown*, which captures borrowers' relative optimism about the downside, remains insignificantly related to collateral value. Columns (5) and (6) show that these results remain robust after including additional controls for the belief distribution.

In summary, we infer belief distributions for borrowers and lenders from textual data and construct measures of cross-sectional belief disagreement across investor groups. The results are consistent with our theoretical predictions: collateral value increases with belief disagreement, particularly when disagreement concerns the upside state. These findings provide further support for Hypothesis 3.

6 Conclusion

Despite extensive theoretical work on collateral value, identifying its existence and determinants in real-world financial markets remains empirically challenging. This paper exploits the unique institutional setting of Chinese structured funds, which split a parent fund into a senior (A) tranche and a junior (B) tranche. This structure allows us to infer collateral value directly from observable fund premia. Using this setting, we provide direct empirical evidence on how leverage generates collateral value and how belief disagreement shapes its magnitude.

Our empirical analysis yields three main findings. First, collateral value is positive and economically significant. Second, collateral value increases with leverage. Using the parent fund NAV as an instrumental variable and exploiting exogenous leverage changes around restructuring events, we provide causal evidence that higher leverage leads to larger collateral value. Third,

the shadow value of leverage depends on both the level and the nature of belief disagreement. Using both survey-based and text-based measures, we show that greater disagreement increases collateral value per unit of leverage. Importantly, the nature of disagreement is central: optimism about upside states significantly raises collateral value, whereas optimism about downside states has little effect.

By exploiting rich time-series and cross-sectional variation in leverage, this paper complements existing empirical work that primarily relies on one-time policy shocks. More broadly, we provide new evidence on how heterogeneous beliefs shape the value of leverage and offers direct empirical support for the mechanism in Simsek (2013). Our findings show that leverage and belief disagreement jointly shape asset prices. When investors disagree, especially about upside outcomes, the borrowing capacity embedded in leveraged contracts becomes more valuable. These results highlight a mechanism through which disagreement amplifies the effects of leverage on asset prices and have implications for the design and regulation of leveraged financial products.

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Figures and Tables

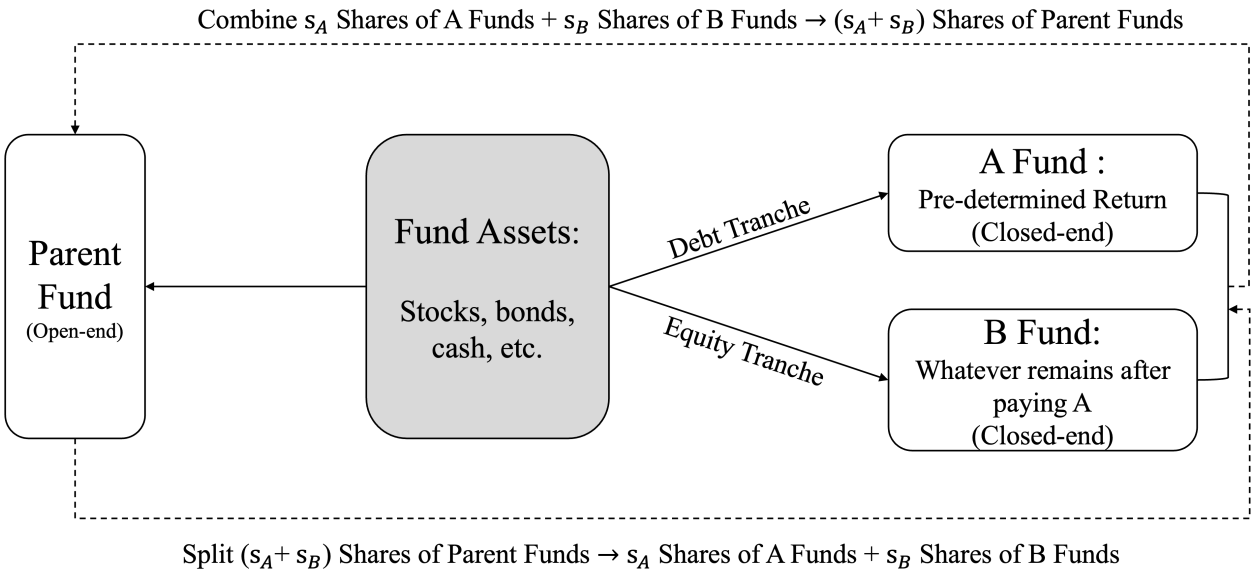
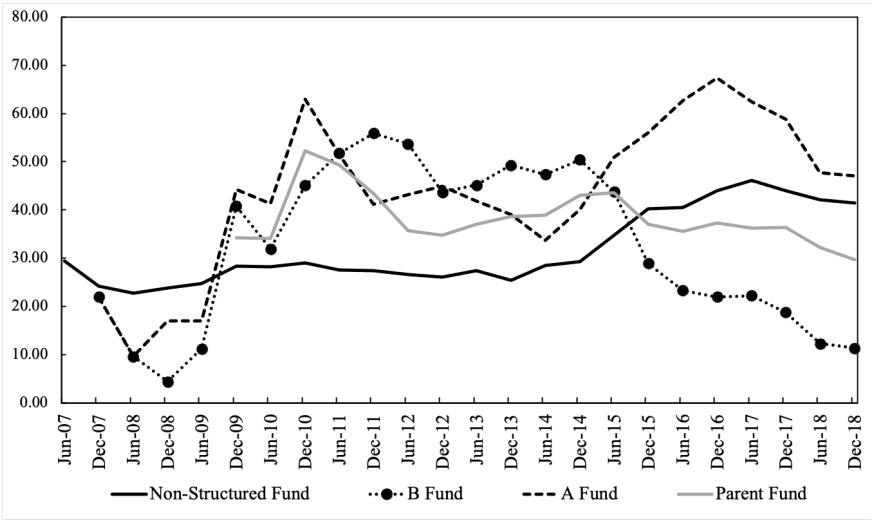
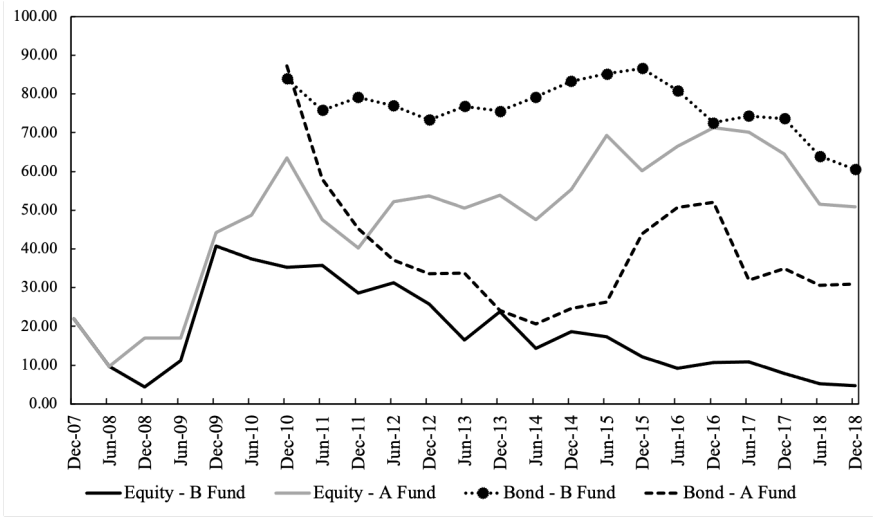


Figure 1: Tranche Structure of Chinese Structured Funds

This figure illustrates the tranche structure of Chinese structured funds. A typical structured fund consists of three components: the parent fund, the A fund (debt tranche), and the B fund (equity tranche). The parent fund is typically open-end, whereas the A and B funds are generally closed-end exchange-traded funds. The net asset value (NAV) of the parent fund reflects the value of the underlying assets. The NAV of the A fund accrues at a predetermined rate of return, while the NAV of the B fund represents the residual claim on the underlying assets after payments to A-fund investors. The dashed lines between the parent fund and the A/B funds denote the paired conversion mechanism, which allows investors to split parent fund shares into A and B shares, or combine A and B shares into parent fund shares.



(a) Institutional Ownership



(b) Institutional Ownership: Equity and Bond Funds

Figure 2: Institutional Ownership of the Chinese Structured Funds

This figure reports the investor composition of structured funds. Panel (a) shows the average institutional ownership for non-structured funds, parent funds, A funds, and B funds. Panel (b) further decomposes A and B funds into equity and bond funds and reports the average institutional ownership for each subtype.

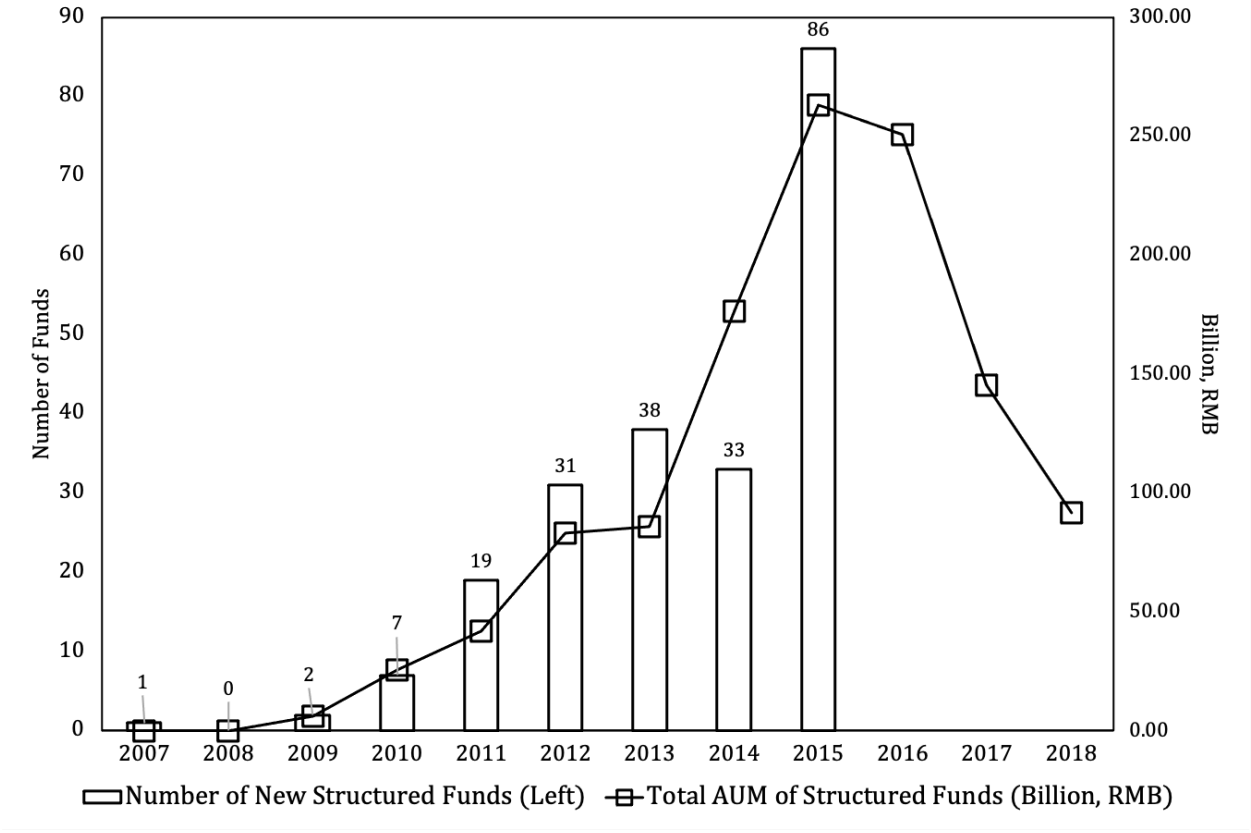


Figure 3: The Chinese Structured Fund Offers and Market Size

This figure shows the number of new structured fund offers each year (the bars) and the total assets under management (AUM) of all structured funds at year-ends (connected squares).

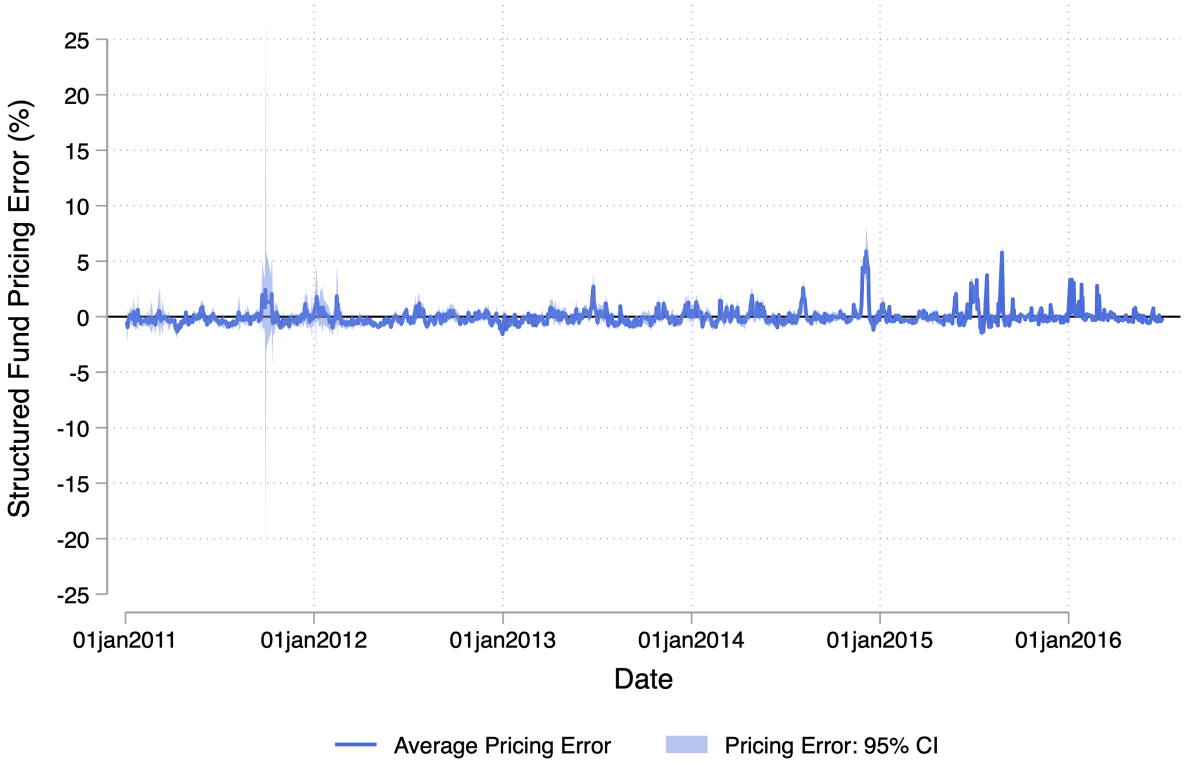


Figure 4: Pricing Error of the Structured Funds

This figure plots the average daily pricing errors of structured funds. We define the pricing error as the percentage deviation between the market value of the A and B tranches and the net asset value (NAV) of the parent fund implied by the conversion ratio. Specifically, if a fund has an initial A–B share allocation ratio of $s_A : s_B$, investors can combine s_A shares of the A fund and s_B shares of the B fund to obtain $s_A + s_B$ shares of the parent fund. The pricing error is therefore defined as $[s_A p_A + s_B p_B]/[(s_A + s_B)NAV_P] - 1$. For each trading day, we compute the cross-sectional average pricing error and the corresponding 95% confidence interval across all structured funds and plot the resulting time series.

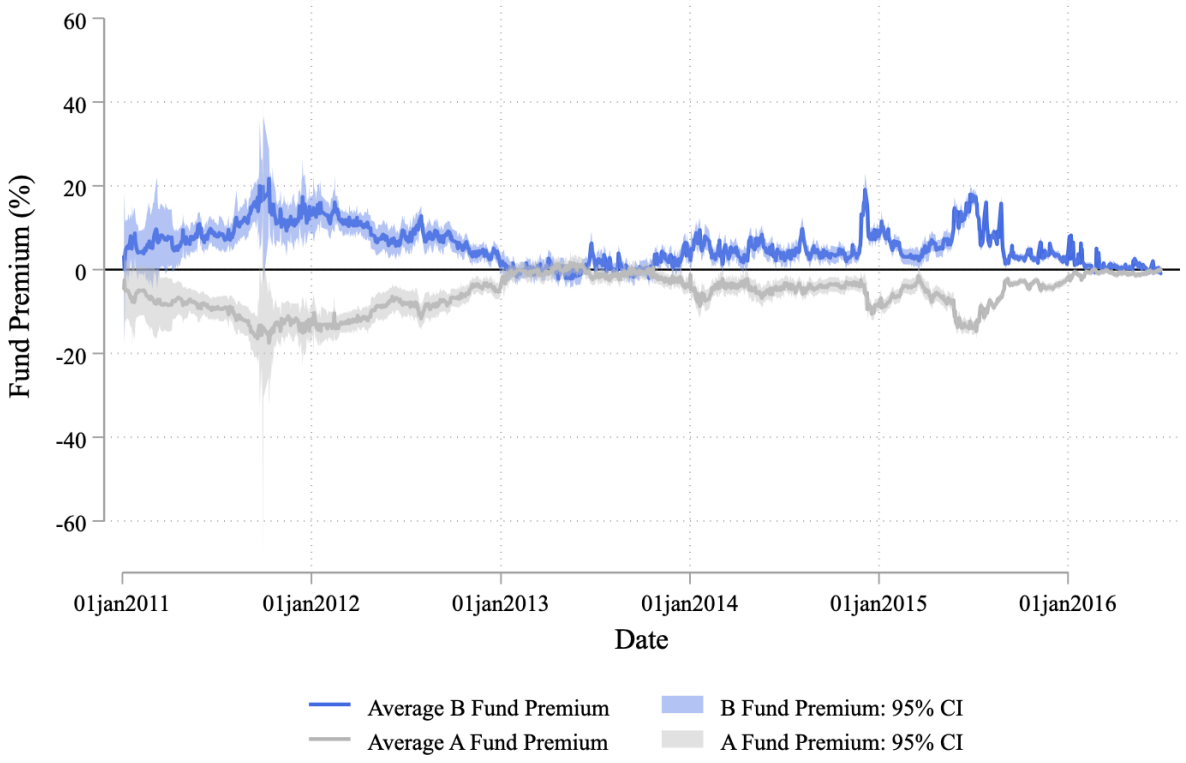
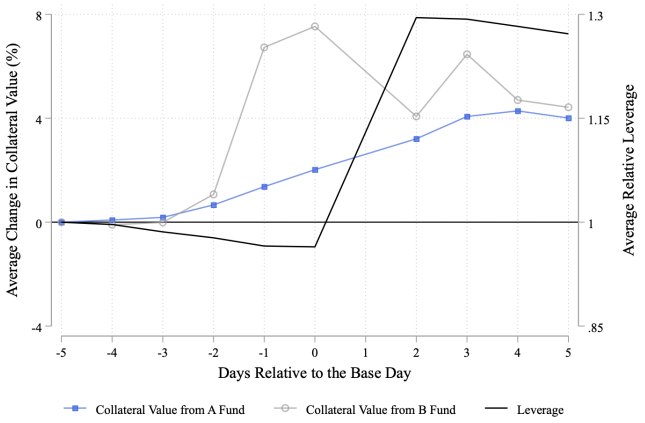
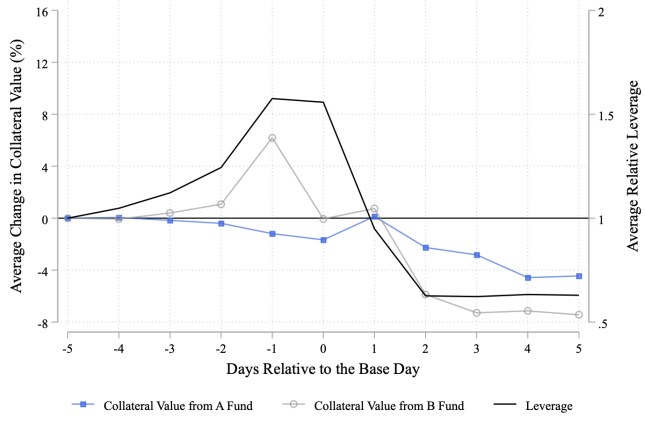


Figure 5: A and B Fund premia

This figure plots the daily average premia of A and B funds along with their 95% confidence intervals. The premium is defined as $(p - NAV)/NAV$, where p and NAV stand for market price and net asset value per share of the funds. The B-fund premium is rescaled to reflect the pricing deviation per RMB of A-fund value. For each trading day, we compute the cross-sectional average A-fund and B-fund premia across all structured funds.



(a) Ascending Restructurings



(b) Descending Restructurings

Figure 6: Collateral Value Dynamics Around Restructuring Events

This figure shows changes in collateral value inferred from A- and B-fund premia over the [-5,5] trading-day window surrounding restructuring events. The premium is defined as $(P - NAV)/NAV$, where P and NAV denote the market price and net asset value per share. The B-fund premium is rescaled to measure the pricing deviation per RMB of A-fund value. Collateral value inferred from the A fund equals the negative of the A-fund premium, while that inferred from the B fund equals the B-fund premium. Day 0 is the restructuring reference date (based on the end-of-day NAV), and day 1 is the first trading day after restructuring. Panels (a) and (b) report median relative changes in collateral value and leverage for ascending and descending restructurings, respectively (relative to their levels on day -5). The solid black line (right axis) represents median relative leverage, while the gray circles and blue squares denote median collateral value changes inferred from A and B funds. Medians are computed cross-sectionally across events for each event day.

Table 1: Institutional Features of the Structured Funds

This table summarizes the institutional features of Chinese structured funds. Panel A describes the characteristics of the parent fund and the A and B tranches. Panel B reports fund-level summary statistics. The first column presents the average leverage at issuance across equity, bond, and hybrid funds. The remaining columns report the number of funds with specific features, including eligibility for paired conversion and index-tracking status.

Panel A. Parent Fund and the A/B Funds			
Characteristics	Parent Fund	A Fund	B Fund
Fund Type	Open-end	Closed-end	Closed-end
Determinants for NAV	Value of underlying fund assets	Pre-determined interest rate	The residual payment of underlying fund assets after paying A fund investors
Primary Market Redemption and Purchase (Stand-Alone)	Yes	No	No
Secondary Market Trading	Mostly No	Yes	Yes

Panel B. Features of the Structured Funds						
	Leverage at Issuance	Number of Funds				
		Conversion		Index Fund		Total
		Yes	No	Yes	No	
Equity Fund	1.972	146	2	146	2	148
Bond Fund	3.279	7	60	3	64	67
Hybrid Fund	1.429	2	0	0	2	2
Total	2.237	155	62	149	68	217

Table 2: Summary Statistics

This table reports summary statistics for structured funds (Panel A) and belief distributions (Panels B and C). Panel A presents fund-day-level statistics. Subscripts P, A, and B denote the parent, A, and B funds. NAV, P, and Prem denote daily net asset value, price, and premium, where Prem = $(p - NAV)/NAV$. The B-fund premium is rescaled to measure the pricing deviation per RMB of A-fund value. For the parent fund, PceError is the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. For index funds, we report the index level (scaled by 1000) and tracking error (TrackError). Leverage is defined as the asset-to-equity ratio. Variables are trimmed at the 1% and 99% levels. Collateral value inferred from the A fund (Cola_A) equals the negative of the A-fund premium, while Cola_B equals the B-fund premium. UnitCola_A (UnitCola_B) scales Cola_A (Cola_B) by leverage. Panel B reports year-month belief distributions from survey data conducted by the China Securities Investor Protection Fund Corporation. ProbUp, ProbNeut, and ProbDown denote the fractions of respondents expecting the market to rise, remain unchanged, or decline over the next month. RelaUp is defined as ProbUp/(1-ProbDown). Dispersion and Entropy measure belief dispersion and are defined as $1/(\sum_{k=Up,Neut,Down} \text{Prob}_k^2)$ and $-\sum_{k=Up,Neut,Down} \text{Prob}_k \log(\text{Prob}_k)$, respectively. Panel C reports belief distributions inferred from text data. Retail (borrower) beliefs are extracted from social media posts, and institutional (lender) beliefs from financial news. Beliefs are aggregated to the index-day level using index weights. ProbUp_Borrower (ProbNeut_Borrower, ProbDown_Borrower) and ProbUp_Lender (ProbNeut_Lender, ProbDown_Lender) denote the corresponding probabilities. AvgOpt is the average of ProbUp and ProbNeut across both groups. DTV is the total variation distance between borrower and lender beliefs, defined as $0.5 \sum_{k=Up,Neut,Down} |\text{Prob}_k\text{_Borrower} - \text{Prob}_k\text{_Lender}|$. RelaUp_Text equals ProbUp_Borrower/ProbUp_Lender, and RelaDown_Text equals ProbDown_Lender/ProbDown_Borrower. Both are normalized to obtain RelaUp_Scaled and RelaDown_Scaled.

Panel A. Fund-day Level								
		No. of obs	No. of Funds (Indexes)	Mean	Median	s.d.	p5	p95
Parent Fund	NAV_P	62,929	145	1.004	0.996	0.185	0.727	1.355
	PceError (%)	62,929	145	0.048	-0.350	1.555	-1.517	3.050
	Index	52,785	131	3.739	3.060	2.415	0.902	8.782
	TrackError (%)	52,961	131	-0.0141	-0.007	0.276	-0.396	0.366
A Fund	NAV_A	62,929	145	1.025	1.018	0.029	1.002	1.063
	p_A	62,929	145	0.982	0.982	0.075	0.858	1.111
	Prem_A (%)	62,929	145	-4.249	-3.700	6.514	-15.61	6.350
	Cola_A (%)	62,929	145	4.249	3.700	6.514	-6.350	15.61
	UnitCola_A (%)	62,929	145	2.270	1.702	3.615	-3.189	9.062
B Fund	NAV_B	62,929	145	0.984	0.972	0.359	0.441	1.664
	p_B	62,929	145	1.031	0.999	0.361	0.484	1.717
	Leverage	62,929	145	2.104	1.977	0.531	1.499	3.241
	Prem_B (%)	62,929	145	4.277	3.638	7.215	-7.130	16.78
	Cola_B (%)	62,929	145	4.277	3.638	7.215	-7.130	16.78
	UnitCola_B (%)	62,929	145	2.301	1.670	4.050	-3.622	9.591
Panel B. Survey-based Belief (Year-month Frequency)								
ProbUp (%)		35	-	31.23	30.18	9.292	16.59	50.41
ProbNeut (%)		35	-	37.84	32.44	11.49	25.57	55.50
ProbDown (%)		35	-	30.93	28.81	11.80	11.67	53.09
RelaUp (%)		35		45.51	46.07	11.58	23.78	62.32
Dispersion		35	-	2.711	2.767	0.210	2.366	2.956
Entropy		35	-	1.042	1.057	0.046	0.951	1.091

Panel C. Text-based Belief (Index-day Frequency)							
ProbUp_Borrower (%)	30,792	74	30.42	30.74	5.927	19.52	38.63
ProbNeut_Borrower (%)	30,792	74	44.02	44.44	8.905	30.02	54.61
ProbDown_Borrower (%)	30,792	74	22.94	23.89	5.280	9.905	29.06
ProbUp_Lender (%)	30,792	74	25.15	24.48	12.35	0.628	46.52
ProbNeut_Lender (%)	30,792	74	11.92	11.62	6.329	0	22.69
ProbDown_Lender (%)	30,792	74	16.14	13.94	10.97	0.328	37.74
AvgOpt (%)	30,792	74	55.76	56.58	9.742	37.00	70.73
DTV (%)	30,792	74	27.23	25.73	9.558	13.92	49.42
RelaUp_Text	29,593	74	3.545	1.207	31.70	0.598	3.153
Reladown_Text	30,792	74	0.801	0.616	0.880	0.014	2.000
RelaUp_Scaled	29,593	74	0.000	-0.074	1	-0.093	-0.012
RelaDown_Scaled	30,792	74	0.000	-0.211	1	-0.894	1.363

Table 3: Average Collateral Value Inferred from A and B Funds

This table reports the average collateral value inferred from A and B funds across different fund groups, along with statistical significance. Collateral value inferred from the A fund (Cola_A) equals the negative of the A-fund premium, while Cola_B equals the B-fund premium. Fund premium is defined as the percentage deviation of fund price from its net asset value per share, i.e., $(P - NAV)/NAV$. The B-fund premium is rescaled to measure the pricing deviation per RMB of A-fund value. Results are reported for the full sample, by underlying asset type, and by index status. T-tests are conducted to assess whether collateral values are significantly positive. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Mean	Cola_A	Cola_B
Whole Sample	4.249***	4.277***
Equity Fund	4.222***	4.268***
Bond Fund	5.380***	5.381***
Hybrid Fund	1.942***	1.223***
Index Fund	4.281***	4.424***
Non-index Fund	2.572***	2.411***

Table 4: Leverage and Collateral Value

This table examines the relationship between collateral value and leverage. Collateral value inferred from the A fund (Cola_A) equals the negative of the A-fund premium, while Cola_B equals the B-fund premium. The premium is defined as $(P - NAV)/NAV$. The B-fund premium is rescaled to measure the pricing deviation per RMB of A-fund value. Leverage is defined as the asset-to-equity ratio. Columns (1)–(3) use the full sample of structured funds. Column (1) reports first-stage results relating parent-fund net asset value (NAV_P) to leverage. Columns (2)–(3) report two-stage least squares (2SLS) estimates of the effect of leverage on collateral value, instrumenting leverage with NAV_P. Columns (4)–(6) restrict the sample to index funds and use the index level as the instrument for leverage. All specifications control for PceError, the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. Columns (1)–(3) include fund and trading-day fixed effects, while Columns (4)–(6) additionally include index × year-week fixed effects. Standard errors are clustered at the fund level and reported in the parentheses. The Kleibergen–Paap rk LM statistic tests for under-identification, and the rk Wald F statistic tests for weak instruments. Both statistics are reported at the bottom of the table. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Whole Sample			Index Funds		
	1st Stage	2SLS		1st Stage	2SLS	
	Leverage	Cola_A	Cola_B	Leverage	Cola_A	Cola_B
	(1)	(2)	(3)	(4)	(5)	(6)
NAV_P	-1.747***					
	(0.09)					
Leverage		3.883***	3.695***		6.497***	2.949*
		(0.69)	(0.69)		(1.88)	(1.75)
IndexClose				-0.131***		
				(0.02)		
PceError	-0.032***	0.049	2.021***	-0.016***	-0.109***	1.813***
	(0.00)	(0.04)	(0.05)	(0.00)	(0.04)	(0.05)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes	Yes	Yes
Index × Year-week FE	No	No	No	Yes	Yes	Yes
No. of obs	62,929	62,929	62,929	52,482	52,482	52,482
p-value of Kleibergen-Paap rk LM statistic		0.000			0.000	
Kleibergen-Paap rk Wald F statistic		339.355			32.118	

Table 5: Leverage and Collateral Value: DiD Analysis around Restructuring Events

This table examines the effect of leverage on collateral value using a difference-in-differences (DiD) design around ascending (Panel A) and descending (Panel B) restructuring events. The sample is restricted to the [-5,5] window surrounding restructuring events for treated and control funds. Treated funds are those that undergo restructuring, while control funds are non-restructured funds with triggering-day NAVs close to the restructuring threshold. The interaction term Treat × Post equals one for treated funds in post-restructuring days and zero otherwise. For ascending restructurings, control funds have base-day parent-fund NAV between 1.4 and 1.5 (or between 1.3 and 1.5 in Columns (5)–(8)). For descending restructurings, control funds have base-day B-fund NAV between 0.25 and 0.35 (or between 0.25 and 0.5 in Columns (5)–(8)). All specifications control for PceError, defined as the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. Fund and trading day fixed effects are included in all regressions. Standard errors are clustered at the fund level and reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A. Ascending Restructurings

	Control Fund Base Day $NAV_P > 1.4$			Control Fund Base Day $NAV_P > 1.3$		
	Leverage	$Cola_A$	$Cola_B$	Leverage	$Cola_A$	$Cola_B$
	(1)	(2)	(3)	(4)	(5)	(6)
Treat × Post	0.306***	2.407***	4.523***	0.251***	2.985***	6.333***
	(0.02)	(0.54)	(0.84)	(0.01)	(0.53)	(0.91)
PceError	-0.009***	0.014	0.201***	-0.010***	0.016	0.262***
	(0.00)	(0.01)	(0.03)	(0.00)	(0.01)	(0.03)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Events	51	51	51	52	52	52
No. of obs	2,271	2,271	2,271	6,382	6,382	6,382
Adjusted R^2	0.846	0.893	0.742	0.838	0.896	0.768

Panel B. Descending Restructurings

	Control Fund Base Day $NAV_B < 0.35$			Control Fund Base Day $NAV_B > 0.5$		
	Leverage	$Cola_A$	$Cola_B$	Leverage	$Cola_A$	$Cola_B$
	(1)	(2)	(4)	(5)	(6)	(8)
Treat × Post	-0.990***	-0.101	-4.073***	-0.994***	-0.557***	-3.420***
	(0.08)	(0.24)	(0.56)	(0.05)	(0.18)	(0.43)
PceError	-0.065***	-0.011	0.191***	-0.056***	-0.007	0.569***
	(0.00)	(0.01)	(0.04)	(0.00)	(0.02)	(0.06)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Events	82	82	82	84	84	84
No. of obs	6,656	6,656	6,656	21,652	21,652	21,652
Adjusted R^2	0.744	0.948	0.885	0.744	0.941	0.884

Table 6: Level of Belief Disagreement and Collateral Value: Survey Evidence

This table examines the relationship between belief disagreement and collateral value using survey data from the China Securities Investor Protection Fund Corporation. Dispersion and Entropy measure belief disagreement and are defined as $1/\sum_{k=Up,Neut,Down} \text{Prob}_k^2$ and $-\sum_{k=Up,Neut,Down} \text{Prob}_k \log(\text{Prob}_k)$, respectively. ProbUp, ProbNeut, and ProbDown denote the proportions of respondents expecting the market to rise, remain unchanged, or decline over the next month. The key independent variables are the collateral value per unit of leverage inferred from A and B funds (UnitCola_A and UnitCola_B). All specifications control for PceError, the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. Fund fixed effects are included in all regressions. Standard errors are clustered at the fund level and reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	UnitCola_A		UnitCola_B	
	(1)	(3)	(2)	(4)
Dispersion	9.001***		8.538***	
	(2.13)		(2.11)	
Entropy		28.243***		26.790***
		(8.43)		(8.34)
PceError	0.176**	0.176**	2.445***	2.445***
	(0.08)	(0.08)	(0.14)	(0.14)
Fund FE	Yes	Yes	Yes	Yes
No. of obs	38,364	38,364	38,364	38,364
Adjusted R^2	0.321	0.312	0.388	0.382

Table 7: Nature of Belief Disagreement and Collateral Value: Survey Evidence

This table investigates how the nature of belief disagreement matters for collateral value, using survey data from the China Securities Investor Protection Fund Corporation. ProbUp and ProbDown denote the proportions of respondents expecting the market to rise and decline over the next month, respectively. RelaUp is defined as ProbUp/(1-ProbDown). The key independent variables are the collateral value per unit of leverage inferred from A and B funds (UnitCola_A and UnitCola_B). All specifications control for PceError, the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. Fund fixed effects are included in all regressions. Standard errors are clustered at the fund level and reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	UnitCola_A			UnitCola_B		
	(1)	(2)	(3)	(4)	(5)	(6)
ProbUp	0.168***			0.160***		
	(0.02)			(0.02)		
ProbDown		0.007			0.006	
		(0.03)			(0.03)	
RelaUp			0.219***			0.210***
			(0.03)			(0.03)
PceError	0.282***	0.169*	0.329***	2.547***	2.439***	2.591***
	(0.08)	(0.09)	(0.07)	(0.13)	(0.13)	(0.14)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	38,364	38,364	38,364	38,364	38,364	38,364
Adjusted R^2	0.320	0.299	0.343	0.388	0.372	0.406

Table 8: Level of Belief Disagreement and Collateral Value: Text-based Evidence

This table investigates how the level of belief disagreement matters for collateral value, using beliefs inferred from text data. The key independent variables are the collateral value per unit of leverage inferred from A and B funds (UnitCola_A and UnitCola_B). Retail (borrower) beliefs are extracted from social media posts, and institutional (lender) beliefs from financial news. Beliefs are aggregated to the index-day level using index weights. ProbUp_Borrower (ProbNeut_Borrower, ProbDown_Borrower) and ProbUp_Lender (ProbNeut_Lender, ProbDown_Lender) denote the corresponding probabilities. DTV is the total variation distance between borrower and lender beliefs, defined as $0.5 \sum_{k=Up,Neut,Down} |\text{Prob}_k\text{_Borrower} - \text{Prob}_k\text{_Lender}|$. AvgOpt is the average of ProbUp and ProbNeut across both groups, representing the average optimism of the market. All specifications control for PceError, the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. Fund and trading day fixed effects are included in all regressions. Standard errors are clustered at the fund level and reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	UnitCola_A		UnitCola_B	
	(1)	(2)	(3)	(4)
DTV	3.794**	3.754**	3.383	3.319*
	(1.83)	(1.77)	(2.04)	(1.95)
AvgOpt		0.036*		0.058**
		(0.02)		(0.02)
PceError	0.059	0.062	2.817***	2.822***
	(0.07)	(0.07)	(0.15)	(0.15)
Fund FE	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes
No. of obs	47,649	47,649	47,649	47,649
Adjusted R^2	0.716	0.717	0.701	0.702

Table 9: Nature of Belief Disagreement and Collateral Value: Text-based Evidence

This table investigates how the level of belief disagreement matters for collateral value, using beliefs inferred from text data. The key independent variables are the collateral value per unit of leverage inferred from A and B funds (UnitCola_A and UnitCola_B). Retail (borrower) beliefs are extracted from social media posts, and institutional (lender) beliefs from financial news. Beliefs are aggregated to the index-day level using index weights. ProbUp_Borrower (ProbNeut_Borrower, ProbDown_Borrower) and ProbUp_Lender (ProbNeut_Lender, ProbDown_Lender) denote the corresponding probabilities. DTV is the total variation distance between borrower and lender beliefs, defined as $0.5 \sum_{k=Up,Neut,Down} |\text{Prob}_k\text{_Borrower} - \text{Prob}_k\text{_Lender}|$. All specifications control for PceError, the percentage deviation between the market value of the A and B tranches and the NAV implied by the conversion ratio. Fund and trading day fixed effects are included in all regressions. Standard errors are clustered at the fund level and reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A.						
	UnitCola_A					
	(1)	(2)	(3)	(4)	(5)	(6)
ProbUp_Borrower	0.073*	0.071*				0.071*
	(0.04)	(0.04)				(0.04)
ProbDown_Borrower	-0.020	-0.016				-0.030
	(0.04)	(0.04)				(0.04)
ProbUp_Lender		0.012				
		(0.01)				
ProbDown_Lender		0.011				
		(0.01)				
RelaUp			0.061**		0.062**	0.064**
			(0.03)		(0.03)	(0.03)
RelaDown				0.055	0.037	0.051
				(0.09)	(0.09)	(0.07)
DTV			3.475*	3.691*	3.417*	2.848**
			(1.84)	(1.89)	(1.91)	(1.31)
PceError	0.066	0.064	0.042	0.058	0.041	0.047
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	47,649	47,649	44,118	47,649	44,118	44,118
Adjusted R^2	0.716	0.717	0.704	0.716	0.704	0.705

Panel B.

	UnitCola$_B$					
	(1)	(2)	(3)	(4)	(5)	(6)
ProbUp_Borrower	0.099**	0.096**				0.100**
	(0.05)	(0.05)				(0.05)
ProbDown_Borrower	-0.044	-0.039				-0.054
	(0.05)	(0.05)				(0.05)
ProbUp_Lender		0.017*				
		(0.01)				
ProbDown_Lender		0.002				
		(0.01)				
RelaUp			0.062**		0.063**	0.065**
			(0.03)		(0.03)	(0.03)
RelaDown				0.044	0.038	0.049
				(0.10)	(0.10)	(0.08)
DTV			3.091	3.301	3.031	2.384*
			(2.08)	(2.11)	(2.15)	(1.43)
PceError	0.066	0.064	0.042	0.058	0.041	0.047
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Trading Day FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of obs	47,649	47,649	44,118	47,649	44,118	44,118
Adjusted R^2	0.716	0.717	0.704	0.716	0.704	0.705