Financially Sophisticated Firms:
A Demand-Based Approach to Corporate Financing

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Abstract

Using a newly comprehensive dataset that merges firm-level information with corporate bond issuance and holdings, we show that firms strategically use bond issuance not only to minimize their cost of capital but also to diversify their investor base. Investors' specific demand for certain bond characteristics allows firms to effectively shape their bondholder composition through issuance decisions. We find that firms with more diversified bondholders exhibit increased resilience to credit market shocks. Our analysis underscores the dual function of market timing in corporate bond issuance: firms trade off between reducing capital costs and diversifying their credit supply. Our findings bridge traditional asset pricing and corporate finance models by highlighting that asset supply is endogenous and responds to investors' inelastic demand.

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Company capital structure extends far beyond the simple choice between debt and equity. Firms can issue bonds that vary along characteristics such as seniority, covenants, maturity, and redemption options. They may even issue claims against assets of different subsidiaries. While the corporate finance literature explains debt structures as the firm's attempt to overcome incentive conflicts or information frictions (see for example Rauh and Sufi (2010), Diamond (1991), and Diamond (1993)), we focus on the role of investor demand. Because investors specialize in specific corporate bond characteristics, firms are well positioned to strategically incorporate investor demand when optimizing their capital structure. Market timing in corporate bond issuance increases firm value by reducing cost of capital and by diversifying investor composition, which makes firms more resilient to credit market shocks.

Our contribution is to show evidence of this dual role of market timing. We use an instrumental variable analysis to show that a one standard deviation reduction in credit spreads of a specific bond driven by idiosyncratic investor demand shocks increases issuance by 11% of the median conditional quarterly issuance for that bond type. However, optimizing bond structure involves another crucial dimension: the management of *funding risk*, the firm's exposure to asset-specific risks, including investor demand shocks, that could affect its credit supply. We use a second instrument to show that firms are more likely to issue bonds with lower *demand-based risk* (DBR), our measure for how exposed an asset is to idiosyncratic investor shocks.[1] Diversifying demand-based risk is optimal because it correlates with greater resilience to aggregate credit market shocks. As confirmation of the mechanism, we also show that this financially sophisticated behavior increases both shareholder and enterprise value.

Our findings bridge traditional asset pricing and corporate finance models by highlighting that asset supply is endogenous and capital supply is not perfectly elastic (Baker (2009)). The complexity of the corporate bond market allows corporate managers to cater to investor demands across multiple dimensions, far beyond the simple dichotomy of debt versus equity.[2] Furthermore, by issuing bonds with heterogeneous characteristics, firms mirror the functions of financial intermedi-

[1] This measure is similar in spirit to the stock price fragility in Greenwood and Thesmar (2011). The difference is that DBR is defined at the bond level, and firms' bond portfolio determines their exposure to DBR.

[2] Catering in corporate bond markets extends beyond equity versus bonds (e.g., Baker and Wurgler (2004), Ma (2019)) or variations in maturity structure (e.g., Greenwood et al. (2010)).

aries, facilitating risk sharing among investors (e.g., Allen and Gale (1994)). Understanding this financially sophisticated behavior is particularly crucial in the corporate bond market, which has become a dominant source of credit for the real economy (Buchak et al. (2024)).

Our paper is organized into three main sections. First, we introduce new facts about the corporate bond market, leveraging a newly comprehensive merged dataset that combines Compustat firm financial data with Mergent FISD corporate bond issuance and holdings data. Second, we present a model that highlights the incentives for firms to engage in financial sophistication. Finally, we test the predictions of this model, documenting and quantifying financial sophistication among firms.

Before conducting our empirical analyses, it is essential to reduce the dimensionality of bond heterogeneity to make our study feasible. To achieve this, we categorize corporate bonds into 72 distinct "bond types" based on key characteristics: credit rating, time to maturity, size, redemption options, and covenants. Although this classification does not encompass all possible variations across securities, it accounts for 53% of the price variation observed across all bonds. Notably, the variation in prices across these bond types is not fully explained by the most commonly studied dimensions, such as ratings and maturities, indicating that other dimensions also play a significant role in influencing price variation.

With the bond micro-data mapped to issuer firms and our defined bond types, we document two novel facts. First, a significant portion of firms in our sample demonstrates financial sophistication: 60% of firms issue multiple bond types and 24% issue bonds through multiple subsidiaries as of 2023. This behavior is more common among larger, older firms with higher average credit ratings and lower average credit spreads.

Second, there is a clear pattern of investor specialization by bond type. For example, mutual funds are more likely to hold lower-rated, larger bonds, while insurers predominantly hold larger, longer-term, higher-rated bonds. Interestingly, this heterogeneity is reflected in corporate bond returns: in fact, we find that the returns on bond portfolios of different investors are negatively correlated. To show this, we sort bonds into ratings, maturity and investor holdings buckets. We construct two sets of long-short portfolios that buy bonds mostly held by insurers (mutual funds) and short the bonds least held by insurers (mutual funds). Our analysis reveals a strong negative correlation of -90% in the excess returns of these portfolios. Because our portfolios are roughly neutral in credit spreads and duration, the main two sources of systematic risk in corporate bonds, we attribute at least part of the variation in the returns to idiosyncratic shocks to investors' demand for bonds. The negative correlation reveals that these shocks are not perfectly correlated across investors. This finding suggests that there are market conditions in which mutual funds may be better positioned to lend to firms than insurers, and vice versa. Because current prices of bonds are likely to affect firms' ability to access external finance, it is the firms' best interest to diversify their funding risk - a point we will later show empirical support for.

Inspired by these facts, we present a model to illustrate the mechanism that drives firms toward financial sophistication. The model incorporates heterogeneous, risk-averse investors with idiosyncratic hedging demands. We assume that only firms can issue bonds that enable investors to hedge against these idiosyncratic shocks, as investor portfolios are limited by short-selling and borrowing constraints. Firms strategically optimize their capital structure by considering both the demand curve for specific bonds and the diversification of their investor base. By tailoring the structure of cash flows, firms can create assets that align with investor demand, thereby reducing the cost of capital. However, the incentive to issue high-priced bonds is tempered by the associated exposure to funding risk. We model this funding risk as a quadratic term that reflects the reduced-form cost for external funding, which we assume depends on asset-specific risks, importantly including those stemming from investors' idiosyncratic hedging shocks. As a result, the supply of assets in our model is not exogenous, as is commonly assumed in many asset pricing models, but is instead endogenously determined by value-maximizing firms.

The model delivers four empirically testable hypotheses. The first hypothesis is that idiosyncratic investor demand shocks affect equilibrium prices, either through wealth or preferences. The next two hypotheses are that firms act in a financially sophisticated manner; that is, firms strategically change their debt structure by supplying more bonds of types that either (1) trade at higher prices (lower credit spreads) than other bond types or (2) diversify the firm's credit supply. Our fourth hypothesis is a natural implication: this financially sophisticated behavior increases firm value. We test these hypotheses using 20 years of data on publicly traded U.S. firms.

First, we find that idiosyncratic wealth shocks affect prices. To measure idiosyncratic wealth shocks, we construct two instruments based on mutual fund flows and insurance companies' operating income variation. We orthogonalize fund flows (for mutual funds) and operating income growth (for insurers) with contemporaneous fund and market returns, the VIX, and fund fixed effects. Our identification hypothesis is that the residual flows causes variation in equilibrium credit spread, but are orthogonal to non-observable drivers of bond prices. To isolate variation in prices for a given bond type, we construct a relative credit spread metric that quantifies the divergence in credit spread among different bond types relative to other bond types in the market. We find that bond types that have more net inflows in a given period trade at relatively higher prices. This finding aligns with the demand-based asset pricing literature (Koijen and Yogo (2019)), which demonstrates that asset prices are highly inelastic compared to traditional models, making flows have a significant impact on prices.

Second, we find that firms indeed adjust their bond issuance strategies in response to fluctuations in bond prices, issuing more bonds of types trading at higher prices. To show this, we use the previous result as the first stage of an instrumental variable analysis. Specifically, we instrument the relative credit spread of a specific bond type with the orthogonalized mutual fund flows and insurer operating income growth. This instrument is unlikely to be correlated with firms' fundamentals driving issuance decisions, yet it still exerts a price impact on the bonds it holds (per our first result). We find that firms respond to higher prices in certain bond types by supplying more of those bonds in the next period. The magnitudes are significant: a 1-standard deviation decline in credit spreads for a given bond type increases issuance by 11% of the median conditional quarterly issuance for that bond type. Our results show that firms are price elastic in choosing bond capital structure.

A potential identification concern is that investors direct flows to funds holding bonds of firms with stronger future growth opportunities, thereby anticipating those firms' forthcoming issuances. However, for such behavior to compromise our instrument, it would need to survive our procedure of residualizing flows against contemporaneous returns. That is, investors would need to have private information about firm fundamentals that lead to issuance. As robustness, we verify that our baseline results still hold when we use only flows from retail mutual funds, which are unlikely to be informed about firms' future issuance. Further, we also use variation in selling due to extreme weather events as an alternative instrument for prices, following Ge and Weisbach (2021) and Ge (2022), and find a similar firm issuance response.

Third, we find that financially sophisticated firms actively diversify their funding risk by issuing new bond types with lower demand-based risk. We construct a novel measure called "demand-based risk" (DBR), inspired by our theoretical model. This measure assumes investors' demand shocks follow a one-factor structure, with DBR representing the bond type-specific loading on this factor. We use the first principal component driving variation in observed demand shocks as a proxy for this factor, measured using the exogenous flows calculated in our previous analysis. Our findings reveal that firms tend to issue new bond types with lower DBR, even when controlling for prices. The economic significance is substantial: a 1-standard deviation increase in DBR for a given bond type leads to a decrease in issuance equal to 34.7% of average unconditional quarterly net issuance. Importantly, while firms may prefer to issue bonds with both lower DBR and lower credit spreads, DBR is negatively correlated with credit spreads across assets. This evidence suggests firms face a meaningful tradeoff when selecting bonds to issue: they can either minimize their immediate cost of capital by choosing bond types currently trading at premium prices, or enhance their long-term resilience by issuing bond types that further diversify their funding risk exposure.

Finally, we find support for our fourth hypothesis: firms create value by acting financially sophisticated, and do not increase their risks of financial distress. Using an event study analysis of two-day returns around issuance, we show that issuing more bond types with lower relative credit spreads increases both shareholder value and enterprise value, and does not significantly increase a firm's CDS (a common market-based measure of default risk), while issuing a bond-type with lower DBR reduces the firm's CDS upon issuance. In magnitudes, issuing a relatively more expensive bond type has a net positive two-day abnormal return of 2.7 basis points. A trading strategy that times financially sophisticated issuance daily hence yields an abnormal annualized return of approximately 3.5%.

Central to our argument are two key points. First, because corporate bond prices in the secondary market strongly influence a firm's ability to secure external financing, firms have an incentive to diversify their investor base and reduce funding risks. When bond prices fall in response to a demand shock—such as a specific investor's wealth decline—firms benefit from being able to borrow from other investors. Realizing this advantage requires issuing multiple types of bonds and attracting a broad set of investors. The literature shows that intermediaries tend to trade bonds already familiar to them, especially during times of distress (Zhu, 2021; Barbosa and Ozdagli, 2021). Additionally, due to information asymmetries, investors use bond prices to infer firm fundamentals: a sharp price drop could reflect either poor fundamentals or intermediary-driven liquidity shocks, making it difficult to issue new types of bonds during downturns. Hence, diversifying funding sources in good times helps firms hedge against idiosyncratic shocks and maintain credit access during adverse events. As an example, Ford highlights in its investor presentation that it is "well capitalized with a strong balance sheet; funding diversified across platforms and markets" (see Figure D.1). Second, market frictions ensure that firms themselves function as the marginal producers of assets. Because such frictions prevent other intermediaries from easily replicating a firm's securities (for example, due to short-selling constraints), firms play a pivotal role in determining the supply of these assets, and thus affect equilibrium prices and firm value.

Consistent with our model and findings, we document strong correlations between complex debt structures and firm demand-based risk and resilience. We compute a firm's demand-based risk as its exposure to investors' non-fundamental idiosyncratic shocks by aggregating the demand-based risks of a firm's bonds outstanding to the firm level. Because investors differ in which bonds they hold, there is significant variation in a firm's exposure to demand based risk depending on which bonds they have outstanding. We show that firms with low demand-based risk also have lower return volatility in their overall bond portfolio, consistent with the idea of diversification. We then connect a firm's demand-based risk to its resilience against credit market shocks, measured by its CDS beta relative to the aggregate CDX market. Our findings show that as a firm diversifies its investor base and reduces its demand-based risk, its credit market beta declines, indicating increased resilience. Specifically, within a firm, a one-standard deviation decrease in demand-based risk corresponds to a nearly 6% reduction in its CDS beta relative to the mean.

Next, we provide additional tests in support of our key results. First, we find that investors who previously held large shares of a given bond type disproportionately increase their holdings of that bond type following issuance. This result is in the opposite direction to portfolio diversification motives, supporting the view that there is a scarcity of certain bond types, as investors are not able to satisfy their demand for certain specific bond types. Financially sophisticated firms help to alleviate this constraint. Second, we show that firms with a more concentrated investor base (as measured using the Herfindahl-Hirschman index) have less price dispersion, consistent with the idea that investors value multiple bond characteristics that map into different valuations. Next, we find evidence suggesting that firms face variable adjustment costs and are less likely to borrow from new investors when they are in financial distress. Thus, diversifying their credit supply in normal times is worthwhile to maintain access to more lenders in times of distress.

This paper contributes primarily to four strands of literature. First, we add to the extensive literature on corporate capital structure decisions. One strand links issuance choices to mitigating information asymmetries and agency conflicts: debt maturity influences liquidity risk and signals to investors (e.g., Diamond (1991), Diamond (1993)), debt overhang (Myers (1977), Diamond and He (2014)), strategic default timing (He and Milbradt (2016)), and collateral and covenant design (Donaldson et al. (2019)). Other studies examine firms' choice between bond markets and banks for ex-post renegotiation flexibility (Stulz and Johnson (1985), Bolton and Scharfstein (1996)) and its interaction with real investment (Morellec et al. (2015)). More recent work shows firms respond to market conditions (Erel et al. (2012), Begenau and Salomao (2019)) and investor demand: issuing equity when overpriced (Baker and Wurgler (2000), Baker and Wurgler (2002), Daniel and Titman (2006)) and debt when cheap (Ma (2019)). There is evidence that firms select debt maturity based on relative rates (Baker et al. (2003), Graham and Harvey (2001),Greenwood et al. (2010)), and that firms issue more bonds in response to investor demand shocks (Siani (2022)), arising for example from safe-asset preferences (Mota (2023)) or insurer premium changes (Kubitza (2023)). Also related is recent work on firms issuing bonds to smooth across maturities given rollover risk (Choi et al. (2018), Dangl and Zechner (2021), Choi et al. (2021)). Our contribution to this literature is twofold: first, we provide micro-level evidence that heterogeneous cash-flow demands shape equilibrium prices and thus firms' bond-structure choices across multiple dimensions of bond heterogeneity. As in Mota (2023), we show market timing relies on demand shocks, not private information. Our second key innovation in this literature is to provide the first direct evidence that firms strategically issue bond types to reduce demand-based risk and maintain financial flexibility, a key determinant of debt policy discussed in CFO surveys (Graham (2022)).

Corporate bond markets are an increasingly important source of capital for the U.S. economy, and a growing number of papers have studied the interaction of the bond market with the real economy (e.g., Darmouni and Siani (2025)). Core to this exercise is the merging of bond data with firm data. Only by refining this merge can we observe rich within-firm variation in bond types and investor holdings. We contribute to work on corporate bond markets by sharing a comprehensive and careful merge between firm-level information in Compustat with bond-level information in Mergent FISD and WRDS Bond Returns. Our map is publicly available so that all researchers in corporate bonds can have a more holistic perspective on which firms are issuing what kinds of bonds.[3] Our empirical analysis thus expands on debt studies such as Rauh and Sufi (2010) and Julio et al. (2007) by incorporating a more holistic view of the firm's overall debt outstanding.

As financial markets shift toward non-bank intermediation, corporates increasingly act as financial intermediaries. On the asset side, certain firms manage complex asset portfolios of long-term Treasuries, corporate bonds, and equity (Duchin et al. (2017), Darmouni and Mota (2024)). We focus on the liabilities side, where firms supply scarce assets and facilitate risk sharing. Our finding that investors buy more of the bond types they already hold implies firms tailor issuance to heterogeneous cash-flow demands, rather than passively raising funds. Investor-driven heterogeneity, from insurer asset insulation (Chodorow-Reich et al. (2020), Coppola (2022)) to mutual fund and other non-bank flows (Ma et al. (2022), Falato et al. (2021), Jiang et al. (2022), Darmouni et al. (2022)), now affect pricing and corporate behavior. Because idiosyncratic shocks are weakly correlated across investors and borrower-lender relationships remain sticky (Chernenko and Sunderam (2014)), firms benefit from diversifying their investor base. There is an analogous concept of holdings-driven fragility in stocks (Friberg et al. (2024); Greenwood and Thesmar (2011)). Our findings also relate to papers showing how intermediaries engineer securities to match investor preferences (Gennaioli et al. (2010), Célérier and Vallée (2017), Lugo (2021), De Jong et al. (2013)) or pool and tranche assets to mitigate informational frictions (Allen and Gale (2004); DeMarzo (2005)), and directly relates to Bisin et al. (2014), who model capital structure with incomplete

[3] If interested, please check the authors' websites.

markets and hedging demand. We extend these ideas by providing empirical evidence that non-financial firms themselves tranche their cash flows into distinct securities to cater to heterogeneous investor demands.[4] Examining corporate financial sophistication matters particularly because non-bank intermediaries increasingly dominate markets (Buchak et al. (2024)), changing how shocks propagate through the financial system and influence real economic outcomes.

A growing literature highlights heterogeneity in investor preferences – departing from the traditional representative-agent view–driven by institutional differences and regulatory constraints (Koijen and Yogo (2019), Vayanos and Vila (2021), Bretscher et al. (2022)). For instance, U.S. insurers, who hold roughly one-quarter of the U.S. corporate bond market, are bound by rating-based capital requirements and significant long-term liability exposures (Becker and Ivashina (2015), Koijen and Yogo (2022), Sen (2023)), and property-casualty insurers adjust toward safer assets following large weather-related losses (Ge and Weisbach (2021)). By contrast, mutual funds, who hold 22% of corporate bonds, face short-term, demand-sensitive liabilities that heighten their exposure to return and liquidity shocks (Goldstein et al. (2017), Chen et al. (2010), Ben-David et al. (2022)) and may be further constrained by investment mandates (Bretscher et al. (2023)). Behavioral biases can also create persistent mispricing (Daniel et al. (2019)). We extend this work by showing that firms, often with guidance from underwriters, actively accommodate these diverse demand pressures by issuing bonds with higher prices and diversifying across securities to reach different investors, thereby endogenizing asset supply in corporate bond markets. Thus, by explicitly linking investor heterogeneity with firm issuance behavior, we bridge new asset-pricing theories emphasizing segmented markets and heterogeneous agents (Koijen and Yogo (2019), Vayanos and Vila (2021)) with classic corporate finance questions about optimal capital structure.

The rest of the paper is organized as following: Section 1 introduces the data and merge. Section 2 outlines how we categorize bonds into bond types, and documents empirical facts about investor composition and variation in bonds issued by the same parent company. Section 3 presents a theoretical framework and develops the testable hypotheses. Section 4 presents our empirical results, Section 5 presents additional tests, and Section 6 concludes the paper.

[4] A related strand examines household financial sophistication. For instance, Calvet et al. (2009) measure under-diversification, risky-share inertia, and the disposition effect.

1 Data and Background

For our empirical analysis, we begin with bond-level information from Mergent FISD and firm-level financial statement information from Compustat. The merge between the two, which has been utilized for many papers in the corporate bond literature, is far from straightforward. One firm in Compustat can merge with many different issuers in FISD, and the match can change over time as companies merge, go through bankruptcy, or spin off subsidiaries. Moreover, the names of subsidiaries that issue bonds may look very different from the name of the ultimate publicly traded parent listed in Compustat. Finally, a parent company and its wholly-owned subsidiaries may all be separately listed in Compustat, so if we map the bonds to the subsidiary issuer but do not attribute them to the parent, we may miss parent-level capital structure decisions.

To address these complications, we begin by merging the two datasets with methods commonly used in the literature, and supplement with string matching and manual matching where needed. We verify our merge, described in detail in Appendix B, with a series of manual checks. As of the end of 2022, the standard WRDS link commonly used to merge Compustat with FISD successfully links 66% of total notional amount of bonds outstanding and 37% of the unique issuing entities. Our final merge instead covers 82% of the total notional amount outstanding and 62% of the issuing entities.[5]

In our analysis, we maintain more bond types and industries than is commonly done in the corporate bond literature, which often excludes facets such as subordinated debt and bonds issued by utility companies. We supplement the core Compustat-FISD merged dataset with bond pricing information from WRDS Bond Returns, bond investor holding data from Refinitiv eMAXX, CDS price data from Markit, quarterly insurer holdings and flows information from NAIC, and stock price and mutual fund flows information from CRSP. We exclude bonds with less than one-year time to maturity, and exclude floating and convertible bonds due to lack of pricing data. Our final dataset includes 22,966 unique bonds issued by 2,558 firms from 2003 Q1 to 2023 Q4.

Bond issuers are not representative of the entire corporate sector. The median bond issuer in

[5] See Appendix B for more details on the merge method and results.

our sample has \$17.1 billion in total assets and \$5.5 billion in total debt in 2023, while the median Compustat firm has \$687 million in total assets and \$97 million in total debt in 2023. Moreover, while the corporate bond market has grown in size significantly, the number of firms accessing bond markets has shrunk from around 1,800 in 2000 to just over 1,400 in 2023 (we show in Figure 1 the time series of both number of firms and the size of the bond market). Thus, in our analysis we will focus on only the subset of firms (that tend to be larger) that act financially sophisticated. Specifically, we consider only non-financial firms (i.e., those with NAICS3 codes other than 521, 522, or 523) with at least \$1 million total assets and book value in the following analyses.

We utilize quarterly corporate portfolio holdings of mutual funds from CRSP, and corporate portfolio holdings of insurers from NAIC. Investors are then grouped into 6 categories: four categories of mutual funds based on the majority of holdings, life insurers, and property and casualty (P&C) insurers. IG mutual funds are defined as those where the maximum share of IG bond holdings is at least 95% over time, otherwise, they are classified as Other funds. Short funds are those where the maximum holdings share in bonds with time to maturity of less then 10 years is 95% or more across time, otherwise, they are classified as Long funds.[6] Note that CRSP provides consistent corporate bond holdings data for most mutual funds only starting in 2010 Q3, so we restrict our sample to the period from 2010 Q3 to 2023 Q4.

To mitigate the impact of abnormal observations and extreme outliers on our empirical results, we implement four truncation steps during the data cleaning process, as documented in Appendix D.2. Our final CRSP and NAIC combined fund-bond-quarter level corporate bond holdings dataset consists of 13,361 unique institutions and 32,855 corporate bonds from 2010 Q3 to 2023 Q4. Table 1 presents the summary statistics of fund (Panel A) and portfolio allocation (Panel B) for each investor category.[7]

Several of our key measures and instruments are derived from fund flows. For mutual funds, we use return and AUM data from CRSP to compute net flows at the individual fund level. For insurance companies, we use operating income and AUM data from NAIC to calculate the year-over-year change in quarterly operating income, which accounts for seasonality. The detailed

[6] See Appendix Table D.1 for the detailed classification of six investor categories.

[7] See Appendix Table D.2 for the share of corporate bonds outstanding held by each investor category.

construction of our exogenous flow measures is provided in Section 4.1.

2 Empirical facts

Our newly merged dataset can speak to the complexity of firms' bond portfolios and map that complexity to investor composition and prices. For example, Exelon Corporation, a large U.S. energy company, issues various types of bonds out of multiple entities. In 2023 alone, the holding company Exelon issued BBB-rated senior unsecured debt in 5-, 10- and 30-year tranches at the coupon rates of 5.15%, 5.3%, and 5.6%, respectively, while three of its subsidiaries issued 10- and 30-year senior secured debt with ratings ranging from A- to AA- at prices ranging from 4.9% to 5.4%. Thus Exelon not only issues bonds out of multiple issuing entities, but also varies the bond characteristics within entities.[8]

Exelon's behavior is not unique. Many firms issue bonds with multiple characteristics, resulting in a very large degree of heterogeneity in bonds. The bond complexity is, in part, a consequence of the firm's history, which includes consolidations, acquisitions, spin-offs, etc. However, even in the time of new issuance, firms tend to issue many bond types at the same time. In an attempt to quantify the heterogeneity of bond structure in a tractable way, we construct a measure of unique bond type based on five dimensions: credit rating, time to maturity, issuance size, covenants, and redemption option. Along the credit rating dimension, we split bonds into A-rated, BBB-rated, and high yield (lower than BBB- rating).[9] We split bonds into three buckets by time to maturity: up to 3 years, 3–10 years, and 10 years or more. We further split bonds into two size buckets by amount outstanding: up to 500 million and 500 million or more.

There are 72 unique bond types in total based on the five dimensions. However, some bond types consistently have no more than 50 unique bonds outstanding in each period of our sample. We then consolidate 18 of these bond types into 6 broader categories, resulting in 60 unique bond types in our final sample. Table 2 documents a detailed categorization and consolidation of the bond types. Table C.1 in the Appendix reports the distribution of the average number of unique

[8]Please refer to Figure D.2 in the Appendix for more details.
[9]We use the combination of Standard & Poor's, Moody's, and Fitch credit ratings.

bonds outstanding per period for all the 60 bond types. While there are other bond characteristics that could shape within-firm price dispersion and the granularity of the buckets could be improved, this classification can explain a significant portion of the variation in credit spreads. To show this, we run panel regressions of credit spreads on increasing groups of fixed effects and report the R-squared of each regression. As a baseline, we first regress credit spreads on month fixed effects $cs_{bt} = \alpha_t + \epsilon_{bt}$, which has an R-squared of 0.127. Replacing the month fixed effect with rating by month fixed effects, the R-squared increases to 0.244. Next we use a rating by month by maturity bucket fixed effect, which increases the R-squared to 0.333. Each additional characteristic increments the R-squared further, and with the full bond type fixed effect as described above, we are able to explain 52.9% of the variation in credit spreads.

2.1 Fact 1: Firms issue multiple bond types

First, we establish that many firms issue multiple bond types, as shown in Figure 2.[10] Firms with multiple bond types tend to be older, larger, better-rated firms that have more bonds as a share of overall debt (see Table 3 for summary statistics of firms with one versus multiple bond types). However, firms are comparable in overall leverage and profitability. Figure D.3 in the Appendix shows that as firms mature, the number of bond types increases. 23% of all firms in our dataset have over 5 bond types outstanding as of 2022. Importantly, firms exploit variation in all dimensions of the bond type classification. 53% of firms on average have bond types in multiple maturity buckets, 37% have bonds in multiple size buckets, 16% have bonds in multiple covenant-lite categories, 20% have bonds in multiple redemption categories, and 6% have bonds outstanding in multiple ratings buckets.

Moreover, 23% of firms in the sample issue out of multiple issuing entities as of 2021 - typically out of 2 unique entities in a given year. This behavior is more common in the utilities, transportation and financial industries- See Table D.3 in the Appendix for more information. While firms with multiple issuing entities tend to be larger, older, and more commonly investment grade, they are similar in average leverage and profitability to firms with only one issuing entity. An unsurprising

[10]Rauh and Sufi (2010) show that firms have many different kinds of debt, like bank vs bonds debt. We focus instead on the heterogeneity among bonds.

but useful implication of this fact is that firms with more bond types also have wider dispersion in bond prices.[11]

2.2 Fact 2: Investors sort into different bond types

Next, we show that investors sort into different bond types. This is a natural implication of the known preferred habitats of institutional investors (Vayanos and Vila (2021)) for certain maturities, credit ratings or duration (Bretscher et al. (2022),Bretscher et al. (2023), Gomes et al. (2021), Acharya et al. (2022)). To show this is true across our bond types, we illustrate a matching of bond types and investor classes in Figure 3. We focus our analysis on mutual funds and insurers because we have comprehensive data on their holdings, and they make up around half of corporate bond investors. Each box represents a bond type, and the shade of the box represents the share of mutual funds that hold that bond type. Clearly, there are "preferred habitats" among bond types. For example, mutual funds show a preference relative to insurers for holding bonds with larger amounts outstanding and lower ratings. On the other hand, longer-duration and higher rated bonds, particularly those smaller than 500 million, are almost exclusively held by insurers. Other bond types, particularly larger, highly rated bonds, have more mixed investor bases.

We further show that the differences in investor bond portfolios are reflected in returns. To test how closely related investor demand shocks are, we perform an asset pricing test. We construct zero investment long-short portfolios of corporate bonds that are exposed to investors' demand and have minimal exposure to systematic risk. To do so, each quarter we place bonds into 9 buckets sorted on ratings (A and above, BBB and High Yield) and time to maturity (0-3y, 3-10y and 10yy). Within each bucket we use holdings information to sort bonds into terciles, according to the share of amount outstanding held by each investor sector (mutual funds and insurance companies). Within each tercile we create value weighted portfolios, and we buy the high holdings share bucket and short the low holdings bucket. Finally, we weight the long and short portfolios equally. The cumulative returns of these of these two portfolios are displayed in the picture below.

A striking picture emerges from this exercise, shown in Figure 4. Portfolios with high exposure

[11] See Section C.2 in the Appendix for more discussion and empirical evidence.

to mutual funds holdings have -90% negative correlation with portfolios with high exposure to insures holdings. This strong negative correlation means that firms that are exposed to these two portfolios can diversify specific sector idiosyncratic shocks. By doing so, firms can minimize the cost of financial distress. What might drive the negative correlation between mutual funds and insurer corporate bond portfolios? The literature has documented that because insurers have long-term liabilities, bonds in their portfolio are less likely to be sold in a downturn (Chodorow-Reich et al. (2020),O'Hara et al. (2022), Coppola (2021)). We show evidence that mutual funds can be "safe hands" too, in particular when insurers are forced to sell bonds upon the downgrading of a firm's credit rating. To show this, we run an event study analysis where we track the weighted average firm-level credit spreads in the months before and after the firm is downgraded from A to BBB. We compare firms that have a higher versus lower than median share of mutual fund holdings in the prior period. Figure D.4 shows that firms with a higher share of mutual funds suffer a lower increase in credit spreads upon downgrade. This analysis shows that there are cases where mutual fund lenders may mitigate the magnitude of a negative shock. This suggests benefits to diversifying among mutual funds and insurers. The literature has documented that because insurers have long-term liabilities, bonds in their portfolio are less likely to be sold in a downturn (Chodorow-Reich et al. (2020),O'Hara et al. (2022), Coppola (2021)). We show evidence that mutual funds can be "safe hands" too, in particular when insurers are forced to sell bonds upon the downgrading of a firm's credit rating. Figure D.4 shows that firms with a higher share of mutual funds suffer a lower increase in credit spreads upon a credit rating downgrade from A to BBB. This suggests benefits to diversifying among mutual funds and insurers.

One implication of this mapping is that the more bond types a firm has outstanding, the more investors it has holding its bonds. Indeed, we show in Figure 5 that in the cross section, firms with more bond types outstanding tend to have more unique investors holding their bonds, controlling for total amount outstanding and time fixed effects.

2.3 Putting the facts together: financially sophisticated firms

We have presented facts that characterize firms and investors in the corporate bond market. Up to this point, the facts are merely correlations observed in the data. In the next section, we write down a model inspired by these stylized facts that demonstrates how a profit-maximizing firm will optimally choose a complex debt structure given heterogeneous and risk averse investors. We then test the implications of the model, and importantly show evidence of firms creating value by acting "financially sophisticated": that is, supplying assets to the market that are in high demand while minimizing their own demand-based risk.

3 Model

In this section, we introduce a model that captures the bond issuance behavior of financially sophisticated firms. We assume that firms have the ability to facilitate risk sharing among investors by issuing bonds whose payoffs correlate with investors' idiosyncratic background risks. Since financially engineering these assets outside the firm is costly (e.g., due to short-selling costs), debt structure has an impact on firms' cost of capital and plays a crucial role in determining the supply of such assets, thereby influencing equilibrium prices. On the other hand, through the same mechanism, idiosyncratic shocks to investors' hedging demand (either wealth or preferences) impact asset prices, making the outstanding bonds that firms have issued exposed to investor demand shocks. Because these shocks can impact refinancing costs, we assume that firms dislike volatility in these shocks that affect their funding risk. In our model, optimal capital structure choice resembles a portfolio allocation problem, in which firms trade off the cost of capital and funding risk.

To emphasize the core innovation of this study, we write down a simple model, abstracting from many aspects of corporate debt structure other than the risk-return trade-off. When we apply the model to the data in the next section, we will address other factors influencing corporate bond issuance decisions and discuss how we account for potential omitted variables that could affect the results. Additionally, we assume that the drivers of investor heterogeneity are exogenous to our model and focus on how this heterogeneity impacts firm behavior.

3.1 Environment

Consider a model with one representative firm and I risk-averse agents that face short-selling and borrowing constraints. Agents face heterogeneous idiosyncratic wealth shocks. There are N risky bonds that are issued at par (each price = 1) and one risk-free saving technology in perfectly elastic supply with interest rates normalized to zero. Each risky asset n has gross return $R(n)$, and excess return $\boldsymbol{r} = \boldsymbol{R} - \boldsymbol{1}$. Aside from risk-free debt, the only other financial assets available are those issued by the firm.

We assume that the covariance structure of returns is driven by K_r factors, $\boldsymbol{f} \in \mathbb{R}^{K_r}$, such that for each asset n

$$r_{t+1}(n) = \mu_t(n) + \boldsymbol{\beta}_t(n)^\top \boldsymbol{f}_{t+1} + \epsilon^r_{t+1}(n), \tag{1}$$

where $\mathbb{E}[f_k] = \boldsymbol{0}$, $\mathbb{E}[\epsilon_r] = \boldsymbol{0}$, $Var(\boldsymbol{R}) = \Sigma_r = \boldsymbol{\beta}^\top \Sigma_f \boldsymbol{\beta} + \Sigma_{\epsilon_r}$, $Var(\boldsymbol{f}) = \Sigma_f$, and $Var(\boldsymbol{\epsilon}^r) = \Sigma_{\epsilon_r} = diag(\boldsymbol{\sigma}^2_{\epsilon_r})$.

For each time t, investors are born with investable wealth W_{it} and are subject to a non-tradable background risk with loading $\boldsymbol{\theta}_{it}$ on the factors $\boldsymbol{f}_{t+1}$. Let ω^f_{it} and $\boldsymbol{\omega}_{it}$ be the portfolio weights on the risk-free assets and the risky assets, respectively. The next-period wealth, W_{it+1}, is:

$$W_{it+1} = W_{it}\left[\omega^f_{it} + \boldsymbol{\omega}^\top_{it} \boldsymbol{R}_{t+1} - \boldsymbol{\theta}^\top_{it+1} \boldsymbol{f}_{t+1}\right]. \tag{2}$$

Agents have mean-variance indirect utility over wealth in period $t+1$ with a risk aversion parameter γ_i. Making the problem of agents essentially static, hence for solving the model, we drop the time subscripts, and write $W_{it+1} = W'_i$. Agents face short-selling constraints and cannot borrow to invest; therefore, their portfolio weights must be non-negative and add up to one. Agents solve:

$$\max_{\omega_i^f \in \mathbb{R}, \boldsymbol{\omega}_i \in \mathbb{R}^N} \quad \mathbb{E}[W_i'] - \frac{\gamma_i}{2}\mathrm{Var}(W_i'), \tag{3}$$

$$\text{s.t.} \quad \mathbf{1}^\top \boldsymbol{\omega}_i + \omega_i^f = 1 \tag{4}$$

$$\omega_{fi} \geq 0 \text{ and } \boldsymbol{\omega}_i \geq \mathbf{0}. \tag{5}$$

We define $\boldsymbol{h} = \mathrm{Cov}(\boldsymbol{R}, \boldsymbol{f}) \in \mathbb{R}^{N \times K_r}$ as the covariance of returns and factors, and Lagrange multipliers $\boldsymbol{\lambda}_i \geq \mathbf{0}$ for the short-selling constraints $\boldsymbol{\omega}_i \geq \mathbf{0}$, and $\lambda_{if} \geq 0$ for the borrowing constraint $\mathbf{1}^\top \boldsymbol{\omega}_i \leq 1$. The optimal portfolio choice, derived in Appendix E, is:

$$\boldsymbol{\omega}_i^* = \frac{1}{\gamma_i W_{i0}} \Sigma_r^{-1} \Big[\boldsymbol{\mu} + \gamma_i W_{i0}\, \boldsymbol{h}\, \boldsymbol{\theta}_i + \frac{1}{W_{i0}} \big(\boldsymbol{\lambda}_i + \lambda_{if} \mathbf{1}\big)\Big] \tag{6}$$

We can then write optimal portfolio choices as a linear function of expected returns, hedging demand, and the Lagrange multipliers:

$$\boldsymbol{\omega}_i^* = \frac{1}{\gamma_i W_{i0}} \Sigma_{\epsilon_r}^{-1} \Big[\boldsymbol{\mu} - \boldsymbol{\beta}^\top \boldsymbol{\kappa}_i + \gamma_i W_{i0}\, \boldsymbol{h}\, \boldsymbol{\theta}_i + \tfrac{1}{W_{i0}} \big(\boldsymbol{\lambda}_i - \lambda_{if}\, \mathbf{1}\big)\Big] \tag{7}$$

where $\kappa_i = D_r\, \beta\, \Sigma_{\epsilon_r}^{-1} \tilde{\boldsymbol{\mu}}_i$, $D_r = \left(\Sigma_f^{-1} + \beta\, \Sigma_{\epsilon_r}^{-1}\, \beta^\top\right)^{-1}$ and $\tilde{\boldsymbol{\mu}}_i = \boldsymbol{\mu} + \gamma_i W_{i0}\, \boldsymbol{h}\, \boldsymbol{\theta}_i + \frac{1}{W_{i0}} \big(\boldsymbol{\lambda}_i - \lambda_{if}\, \mathbf{1}\big)$.

There is also a representative firm that takes bond prices and portfolio allocation as given and chooses a capital structure to maximize its value. Specifically, the firm seeks to finance a profitable investment with cost c that generates certain dividends D. Given the absence of uncertainty in D, this investment could be fully financed with risk-free debt.

However, the firm has an alternative strategy: it can partition the investment into subprojects and issue bonds backed by each component. Under this approach, the firm issues N distinct risky bonds at par value, raising total proceeds of $\boldsymbol{q}^\top \mathbf{1}$, where $\boldsymbol{q} \in \mathbb{R}^N$ represents the vector of issuance quantities across all bonds. Each bond n has specific risk characteristics. Bond n repays $R(n)$ with probability $\pi(n)$, or defaults with complete loss (repaying zero) with probability $1 - \pi(n)$.

The firm also recognizes a funding risk associated with each bond type n. This funding risk comprises two components: investor demand shocks and other bond-specific issuance costs. The investor demand shocks correspond to either preference shocks (θ_{it}) or wealth shocks (W_{it}). Even though the firm's problem is static, we interpret the time series variation in these forces as capturing, in reduced form, the impact of refinancing costs on the firm. The bond-specific issuance costs resemble the reduced-form convex costs used in traditional corporate finance issuance models.

Let $\iota_t(n)$ denote the shocks driving the funding risk of bond n. We assume there are K_ι factors, $\boldsymbol{g_t} \in \mathbb{R}^{K_\iota}$, driving investor demand and a $\epsilon_{\iota t}(n)$ a idiosyncratic cost. The funding risk can be formally expressed as

$$\iota_t(n) = \bar{\iota}(n) + \boldsymbol{\delta}^\top(n)\boldsymbol{g}_t + \epsilon_{\iota t}(n) \tag{8}$$

where $\mathbb{E}[\boldsymbol{g}_t] = \mathbf{0}$, $\mathbb{E}[\boldsymbol{\epsilon}_{\iota t}] = 0$, $Var(\boldsymbol{\iota}_t) = \Sigma_\iota$. $Var(\boldsymbol{g}_t) = \Sigma_g$, and $Var(\boldsymbol{\epsilon}_{\iota t}) = \Sigma_{\epsilon_\iota} = diag(\boldsymbol{\sigma}^2_{\epsilon_\iota})$.

Note that the variation in the demand risk is fundamentally coming from the time variation in investors' preferences and wealth. We just assume that the time-series variance-covariance does not change over time and the firm's problem is static. We think about this approach as a shortcut to model the dynamics driving investors portfolio allocation.

The firm chooses a capital structure to maximize expected value, but its decision is limited by convex costs in raising external funds, as is common in the corporate finance literature. The innovation in our setting is that we make this financing cost dependent on the risk coming from investors' idiosyncratic demand for bonds in the form of funding risk Σ_ι.[12] The firm's objective is to determine the optimal financing strategy by maximizing financing efficiency while managing funding risk. Let $\gamma_f > 0$ be the firm's funding risk aversion. It chooses its debt structure to

[12]We model funding risk in a reduced form for simplicity. These costs may be due to unpredictable liquidity needs arising before the project's output is realized and the inability to raise capital if these coincide with bad wealth realization for investors. Other asset-specific risks that affect issuance costs include for example refinancing risk and covenant risk.

maximize

$$\max_{\boldsymbol{q}\in\mathbb{R}^N} \quad \mathbb{E}[D+\boldsymbol{q}^\top(\mathbf{1}-\boldsymbol{R})] - \frac{\gamma_f}{2}\boldsymbol{q}^\top\Sigma_\iota\boldsymbol{q} \tag{9}$$

$$\text{s.t.} \quad \boldsymbol{q}^\top\mathbf{1} \geq c, \boldsymbol{q} \geq \mathbf{0} \tag{10}$$

$$\boldsymbol{q}^\top(\mathbf{1}-\boldsymbol{R}(s)) + (D-c) \geq 0 \;\forall \text{ all states } s, \tag{11}$$

The first constraint is a funding condition, ensuring that the firm raises c for investment purposes. However, since the firm can always finance both projects by raising c through the risk-free asset, this constraint is never binding and can be disregarded in our analysis. The second constraint is a solvency condition that must hold in all states of the world, meaning the firm can default on one bond while still meeting its obligations on the other; in other words, the bonds are bankruptcy-remote from each other. This constraint is crucial as it differentiates our model from typical debt models, where lenders have a claim on all the firm's assets in the event of default. Nevertheless, since D and γ_f are parameters, we set them such that this constraint will also not bind, so we ignore it in the following discussion. In that case, the optimal issuance decision is:

$$\boldsymbol{q}_S^* = \frac{1}{\gamma_f}\Sigma_\iota^{-1}(\mathbf{1}-\mathbb{E}[\boldsymbol{R}]) = -\frac{1}{\gamma_f}\Sigma_\iota^{-1}\boldsymbol{\mu}, \tag{12}$$

where $\boldsymbol{\mu} = \mathbb{E}[\boldsymbol{R}] - \mathbf{1}$ is an expected (excess) return and Σ_ι represents the funding risk associated with the portfolio of bonds the firm has outstanding. We can then write out supply as a linear function of expected returns and demand-based risk at the asset level n:

$$q^S(n) = \frac{1}{\gamma_f\sigma^2_{\epsilon_\iota}(n)}\left[\mu(n) - \boldsymbol{\delta}^\top(n)\boldsymbol{\kappa}_f\right] \tag{13}$$

where $\kappa_f = D_\iota\boldsymbol{\delta}\,\Sigma_{\epsilon_\iota}^{-1}\boldsymbol{\mu}$, a $K_\iota \times 1$ vector that is importantly constant across assets and $D_\iota = \left(\Sigma_g^{-1} + \delta\,\Sigma_{\epsilon_\iota}^{-1}\,\delta^\top\right)^{-1}$

The firm's problem thus resembles a mean-variance utility, subject to constraints. The "mean" term represents the expected proceeds of the project net of capital expected payouts. The "variance" term is the firm's exposure to the covariance of the asset's risk, which importantly includes the idiosyncratic shocks of the asset holders.

We solve for bond yields such that markets clear. The total quantity of each risky bond j has to equal the amount held across investors i:

$$q(n) = \sum_i q_i(n) \; \forall n \tag{14}$$

We can write the aggregate demand and supply for each asset n as:

$$q^D(n) = \frac{W_0}{\gamma_d \sigma^2_{\epsilon_r}(n)} \Big[\mu(n) + \gamma_d \boldsymbol{h}(n)\bar{\boldsymbol{\theta}} + \bar{\lambda(n)} - \boldsymbol{\beta}^\top(n)\bar{\boldsymbol{\kappa}} \Big] \tag{15}$$

Note that if markets were complete and trading were unconstrained, then the Modigliani-Miller theorem would hold, meaning the firm's value would be independent of its debt structure. This is because once a firm issues a risky bond, investors could construct any desired payoff by combining the risk-free bond with the risky bond, and they would trade until the value of issuing new bonds reaches zero. However, we assume that the firm uniquely holds the ability to issue financial securities with payoffs contingent on the state of the economy, and that short-selling is not an option. Hence, if investors desire these state-contingent payoffs, the firm's financial sophistication can generate additional value.

For simplicity, we assume $W_{i0}\gamma_i = \gamma_d, \forall i$. Using market clearing, we can then solve for optimal firm issuance yields in equilibrium, which leads to:

$$\boldsymbol{\mu} = \left(\frac{1}{\gamma_f} \Sigma^{-1}_{\epsilon_\iota} + \frac{W_0}{\gamma_d} \Sigma_{\epsilon_r} \right)^{-1} \left[\frac{1}{\gamma_f} \Sigma^{-1}_{\epsilon_r} \boldsymbol{\delta}^\top \boldsymbol{\kappa}_f - \frac{W_0}{\gamma_d} \Sigma^{-1}_{\epsilon_r} \left(\gamma_d \boldsymbol{h}\bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}} \right) \right], \tag{16}$$

where $W_0 = \sum_i W_{oi}$ is the total investable wealth in the economy, $\tilde{w}_i = \frac{W_{0i}}{W_0}$ is agent i's share of aggregate wealth. We further define $\bar{\boldsymbol{\theta}} = \sum_i \tilde{w}_i \boldsymbol{\theta}_i$ as the $K_r \times 1$ wealth-weighted average background-risk loading on non-tradable factors, $\bar{\boldsymbol{\lambda}} = \frac{1}{W_0} \sum_i \tilde{\lambda}_i$ is the $N \times 1$ economy-wide tightness trading constraints per unit of wealth, and $\bar{\boldsymbol{\kappa}} = \sum_i \tilde{w}_i \boldsymbol{\kappa}_i$ is the $K_r \times 1$ wealth-weighted average hedge-portfolio that strips out the systematic component of expected returns.

We can write the linear equation for a given asset n:

$$\mu(n) = B_\theta(n) \cdot \bar{\boldsymbol{\theta}}^\top \boldsymbol{h}(n) + B_\lambda(n) \cdot \bar{\boldsymbol{\lambda}}(n) + B_\beta(n) \cdot \boldsymbol{\beta}(n) + B_\delta(n) \cdot \boldsymbol{\delta}(n) \tag{17}$$

where

$$A(n) = \left(\frac{W_0}{\gamma_d \sigma_r^2(n)} + \frac{1}{\gamma_f \sigma_\iota^2(n)} \right)^{-1} \tag{18}$$

$$B_\theta(n) = -A(n) \cdot \frac{W_0}{\sigma_r^2(n)} \tag{19}$$

$$B_\lambda(n) = -A(n) \cdot \frac{W_0}{\gamma_d \sigma_r^2(n)} \tag{20}$$

$$B_\beta(n) = A(n) \cdot \frac{W_0}{\gamma_d \sigma_r^2(n)} \bar{\boldsymbol{\kappa}}^\top \tag{21}$$

$$B_\delta(n) = A(n) \cdot \frac{1}{\gamma_f \sigma_\iota^2(n)} \kappa_f \tag{22}$$

Proofs are in Appendix E.

Note that if $\gamma_f = 0$, thus the firm was unconcerned with funding risk, then the firm could supply infinitely the bonds until prices equal their expected payoff, thus $\mu = 0$, and there would be no value to financial sophistication. Similarly, if agents were risk neutral ($\gamma_d = 0$), then prices would collapse to their expected value, and supply and demand curves become perfectly elastic. However, since agents are risk averse ($\gamma_d > 0$), the equilibrium prices also reflect the agents' collective exposure to the aggregate shock. As investors become more risk averse, represented by a higher γ_d, this hedging motive becomes stronger, and returns change to accommodate the higher demand for hedging.

3.2 Hypothesis development

Hypothesis 1: Investors' hedging needs affect equilibrium prices. Our first hypothesis is that idiosyncratic shocks to wealth (W) or preferences (θ) that impact investor hedging needs affect equilibrium prices. Specifically, when the net demand for an asset increases, the price increases.

This follows from Equation 16:

$$\nabla_{\bar{\boldsymbol{\theta}}}\boldsymbol{\mu} = -\left(\frac{1}{\gamma_f}\,\Sigma_\iota^{-1} + \frac{W_0}{\gamma_d}\Sigma_r\right)^{-1} \cdot \frac{W_0}{\gamma_d}\Sigma_r \cdot \boldsymbol{h} \tag{23}$$

Consider an asset n such that $h_k(n) > 0$, $\forall k$. Therefore, a net increase in the aggregate heading needs, $\bar{\boldsymbol{\theta}}$, leads to a decrease in $\mu(n)$ or, equivalently, a decrease in equilibrium prices.

Hypothesis 2: Prices affect bond supply. Conditional on demand risk, $\boldsymbol{\delta}$, firms will issue more bond types that have lower yields. This is easy to see from Equation 12:

$$\frac{\partial q^S(n)}{\partial \mu(n)} = -\frac{1}{\gamma_f \sigma_\iota^2(n)} < 0.$$

Hypothesis 3: Demand-based risk affects equilibrium prices and bond supply. In the cross-section of bonds, bonds with higher demand-based risk $\boldsymbol{\delta}$ higher yields and/or lower prices. This is easy to see from Equation 12. This creates a tension in the issuance decision of the firm: since assets with higher *dbr* have lower prices, they must trade-off between maximizing proceeds for this issuance versus reducing their funding risk going forward.

As a corollary, conditional on prices, firms will issue more bonds that lower their demand-based risk.

$$\frac{\partial q^S(n)}{\partial \delta(n)} = \frac{1}{\gamma_f \sigma_\iota^2(n)}\kappa_f < 0.$$

Hypothesis 4: Financial sophistication creates value. As long as $\mu < 0$, i.e., there is a heading premium for bonds, there is value in financial sophistication.

4 Empirical tests of the model predictions

In this section, we present our empirical tests of the model's key predictions, which requires isolating an exogenous demand shock that moves bond prices but is orthogonal to firms' own financing fundamentals. Conceptually, the ideal instrument is a pure wealth shock to a large investor that is orthogonal to any firm-level investment or borrowing decisions. For instance, imagine a hurricane strikes a region far from our sample firms but inflicts heavy losses on property insurers, forcing them to liquidate a fixed portfolio (say 70% in bond type A, 30% in type B). This mechanical "fire-sale" would drive up the credit spread of A relative to B (Hypothesis 1), and under our model, firms should respond by issuing fewer A bonds (Hypothesis 2) . If the sales by the property insurers decreases the demand-based risk of both bonds (which would be the case if property insurers have more volatile flows), then a competing force implied by the model would encourage firms to issue less of both bonds (Hypothesis 3). Because hurricanes are exogenous, the resulting insurer outflows are plausibly orthogonal to unobserved firm characteristics, validating the instrument. In practice, we can only implement this insurer fire-sale IV for the ten bond types with the greatest insurer holdings (using methods and data from Ge and Weisbach (2021), Ge (2022)), which we discuss in Section 4.3.4.

To extend our identification to the full set of bond types, our main analysis instead exploits quarter-to-quarter shocks in mutual-fund and insurer flows, residualized for contemporaneous returns and observable investor characteristics, as instruments for both relative yields and demand-based risk. These orthogonalized flow instruments allow us to deliver a clean test of how prices and idiosyncratic demand risk drive firms' strategic issuance choices.

4.1 Investors' hedging needs affect prices

In this section, we test if idiosyncratic investor demand shocks affect prices, controlling for demand-based risk. We construct investor demand shocks by first collecting flows at the individual institution level. For mutual funds, we compute fund's net inflows using cumulative quarterly returns, normalized by AUM from the previous quarter. For insurers, we compute the year-on-year quarterly change in operating income(to control for seasonality) and divide it by AUM from the same quarter one year prior.[13] The detailed data cleaning steps are documented in Appendix D.2.

[13] This is similar in spirit to Darmouni et al. (2022) and van der Beck et al. (2022) for mutual funds and Kubitza (2023) for insurers.

To extract the exogenous component of net flows, we regress net flows for each fund i within investor group g on contemporaneous returns and recover the residuals as orthogonalized flows. We then compute fund-quarter level demand shocks as the deviation of each fund's orthogonalized flow from the average orthogonalized flow at the investor category-quarter level:

$$f_{it}^{g} = \beta^{g} \bar{R}_{it}^{g} + f_{it}^{g,FS,\perp} \tag{24}$$

$$f_{it}^{g,\perp} = f_{it}^{g,FS,\perp} - f_{ct}^{\perp} \tag{25}$$

We residualize net flows separately for each of the three investor groups $g \in$ [Mutual Funds, Life Insurers, P&C Insurers], such that the resulting orthogonalized flow measure, $f_{it}^{g,FS,\perp}$, has a mean of zero within each group and is comparable across investor groups. We then further demean $f_{it}^{FS,\perp}$ at the fund-category level to get $f_{it}^{g,\perp}$. Specifically, fund-category level orthogonalized flows are computed as $f_{ct}^{\perp} = \frac{\sum_{i \in c} f_{it}^{FS,\perp} \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$ for $c \in$ [IG/Long MFs, IG/Short MFs, HY/Long MFs, HY/Short MFs, Life insurers, P&C insurers].[14] The intuition behind this demeaning step is that fund-category level flows in a given period may still be correlated with macroeconomic fundamentals. For example, a surge in flows into IG-long mutual funds might reflect market or firm-level expectations about future long-term IG investment opportunities, and thus also about borrowing conditions. While the first-stage residualization on fund returns likely accounts for much of this common variation, residual flows could still contain fund-category specific components (e.g., IG-long funds). By isolating each fund's deviation from its category's average flow in a given period, we obtain a measure that is more purely idiosyncratic and orthogonal to category-level fundamentals that might otherwise correlates with firm decisions.

We then compute idiosyncratic investor demand shocks for each bond type by aggregating the orthogonalized flows in Equation (25) to the bond type-quarter level:

$$z_{nt}^{cs} = \sum_{i \in I_{nt}} \frac{\omega_{in,t-1} AUM_{i,t-1}}{mktcap_{n,t-1}} \times \hat{f}_{it}^{\perp} = \sum_{i \in I_{nt}} \frac{paramt_{in,t-1}}{amtout_{n,t-1}} \times \hat{f}_{it}^{\perp} \tag{26}$$

[14]See detailed categorization of investor categories in Section 4.3.

where I_{nt} is the set of funds that holds bond type n in period t.[15]

As our main outcome variable, to proxy for prices of bond types, we construct a firm-specific relative credit spread for bond type n across all issuers other than firm f. We exclude credit spreads on the firm's own bonds to better approximate the market-wide price of a given bond type.

$$cs^r_{fnt} = \left(\frac{\overline{cs}_{nt,-f} - \overline{cs}_{t,-f}}{\overline{cs}_{t,-f}}\right) - \frac{1}{12}\sum_{\tau=t-12}^{t-1}\left(\frac{\overline{cs}_{k\tau,-f} - \overline{cs}_{\tau,-f}}{\overline{cs}_{\tau,-f}}\right) \tag{27}$$

where credit spreads on the right-hand side are the averages at the bond type-month level weighted by bonds outstanding in the same period. cs^r_{fnt} thus measures the deviation of a given bond type n's credit spread relative to other outstanding bonds in period t. We remove the firm's own credit spread to avoid the bias arising from omitted variables affecting both a firm's decision to issue a bond type and the price of the firm's bond type. Since some bond types typically have lower credit spreads than other bond types, we demean the price deviation measure using its average over the past 12 months. Higher values of cs^r_{fnt} correspond to relatively higher credit spreads (lower prices).

We test Hypothesis 1 by regressing the relative credit spread measure cs^r_{fnt} on the exogenous flows into bond type n, z^{cs}_{nt}. We control for the bond-type's previous period demand-based risk, Tobin's Q, leverage, average CDS level, the amount of debt due, and log total assets at the firm-quarter level, as well as firm and quarter fixed effects.

$$\begin{aligned} cs^r_{fn,t-1} = {} & \beta z^{cs}_{n,t-1} + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} \\ & + \delta_4 DebtDue_{f,t-1} + \delta_5 log(Assets)_{f,t-1} + \delta_6 dbr_{n,t-1} + \alpha_t + \alpha_f + \epsilon_{fnt} \end{aligned} \tag{28}$$

We present the results in Table 4, and find that positive shocks in exogenous net inflows to a given bond type n reduces a bond type's relative credit spread, even within firm-month. Our preferred specification includes all firm controls and firm and time fixed effects and is reported in column (2): holding all else constant, a 1 standard deviation decrease in a given bond type's exogenous net flows leads to a 0.72 percentage point increase in a firm's relative credit spread of that bond type. This translates into a 0.015% increase in credit spreads compared to the average credit spread of

[15] This method is similar to what is used in Darmouni et al. (2022) and van der Beck et al. (2022), but flow-based estimation of demand curves goes back to Shleifer (1986).

all other firms in that period.

4.2 Firms supply assets in response to investor demand shocks

Next, we test the Hypothesis 2: whether demand shock–driven price changes motivate firms to issue more of those bond types trading at higher prices in the next period. We can exploit the results from the previous section as the first stage of an instrumental variable regression of net issuance on demand shock–driven price changes.

While the results above show that exogenous flows into a bond type (z^{cs}_{nt}) affect prices and thus satisfy the relevance condition to be a valid IV, do they satisfy the exclusion restriction? The primary identification concern would be that some component of the exogenous flows into a given asset is correlated with unobserved firm fundamentals that may drive a firm's decision to issue that asset. However, by construction, the potential endogenous component of the IV would have to be orthogonal to returns, time-invariant fund characteristics, and market-wide movements (see Equation 25). If, for example, certain investors had private knowledge that BBB-rated firms would face difficulties issuing long-duration debt and thus caused outflows from funds holding BBB-rated long-duration bonds, this should already be reflected in the returns for those funds and thus would have been removed from the instrument. Thus, the remaining variation in the instrument reflects exogenous shocks to household wealth and insurer premiums that are very unlikely to be correlated with unobservable fundamentals that affect firm decisions to issue certain bond types.

Equipped with an instrumented relative credit spread cs^r_{fnt}, we can test Hypothesis 2 by running the following second stage instrumental variable (IV) regression:

$$\begin{aligned} issuance_{fnt} = \gamma_1 \hat{cs}^r_{fn,t-1} + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} \\ + \delta_4 DebtDue_{f,t-1} + \delta_5 log(Assets)_{f,t-1} + \alpha_t + \alpha_f + \nu_{fnt} \end{aligned} \tag{29}$$

where we condition on positive net issuance across all bond types N for the firm f in the specified period. Our outcome variable $issuance_{fnt}$ is defined as the percentage change in amount outstanding for a given bond type n issued by the firm f in period t, normalized by total assets of the firm in the previous period $issuance_{fnt} = \frac{amt_{fnt} - amt_{fn,t-1}}{assets_{f,t-1}} \times 100$.[16]

Columns (1) and (2) of Panel (A) in Table 5 show the first stage results. The instrument is relevant, as more net inflows to a given bond type n should reduce its relative credit spread. The second stage estimates in Panel (B) are supportive of our predictions that firms issue more of a bond type when it has a lower relative credit spread in the previous period. The interpretation for specification (5) is the following: all else equal, a 1 standard deviation decrease in a given bond type's relative credit spread leads to a 0.2 percentage point increase in the firm's issuance to assets ratio for that bond type in that month.[17] This is economically significant and represents 11% of median conditional quarterly issuance of a bond type n (about \$94.3 million). We show the OLS results in Table F.1 for comparison, which are near zero or even slightly positive. This is consistent with an attenuating bias, potentially arising from unobserved firm demand for a given bond type coinciding with higher credit spreads.[18]

In summary, we find evidence of the first two predictions of the model: (1) investors' idiosyncratic shocks affect prices, and (2) firms respond to these demand-driven price changes by issuing more of the cheaper bond types. Put another way, firms are actively responding to investor demand shocks for certain kinds of assets by supplying them.

4.3 Demand-based risk affects equilibrium prices and bond supply

Next, we test whether asset-level demand-based risk impacts prices and affects firm issuance decisions. To do this, we construct an empirical counterpart of the model's asset-level demand-based risk parameter $\boldsymbol{\delta}_t$ from equation (8). Our approach assumes a one-factor structure driving demand shocks and computes bond-type level demand-based risk (dbr) as the loading on the first principal component of bond-type-level investor demand shocks.

[16] Note that this measure captures the change in amount outstanding at the bond type level due to issuance and redemptions, thus excludes any changes in amount outstanding due to bonds changing bond types over time. We run the same IV analysis using an alternative measure of issuance that incorporates rolling down of bond types and find qualitatively similar results.

[17] From Table 11, one standard deviation of the relative credit spread cs^r_{fnt} is 0.168, the coefficient estimate is 1.202, so $1.202 \times 0.168 = 0.2$.

[18] For example, in a time of distress, a firm may need to issue a certain bond type that is not necessarily the one with the highest price.

We construct our demand-based risk measure in three steps. First, we build an investor-level demand risk matrix, then transform it to the asset level, and finally extract the common factor through principal component analysis.

Investor-Level Risk Matrix Construction. We begin by constructing an investor-level demand risk matrix Ω, which we assume remains constant over time. This $C \times C$ matrix represents the variance-covariance matrix of demand shocks across our C investor categories. We categorize investors into six groups based on their investment focus: four groups of mutual funds based on the majority of holdings (long investment-grade bonds, short investment-grade bonds, long high-yield, and short high-yield), and two groups of insurers based on primary purpose (life insurers and property and casualty insurers). For each investor category c at time t, we calculate fund-level orthogonal flows $f_{ct}^{\perp}$ by taking the AUM-weighted average of individual fund flows $f_{it}^{\perp}$ within that category, i.e., $f_{ct}^{\perp} = \frac{\sum_{i \in c} f_{it}^{\perp} \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$. The matrix Ω is then computed as the variance-covariance matrix of these category-level orthogonalized flows across time.

we report the time series of $f_{ct}^{\perp}$ in Figure 6 and the estimated Ω in Table 6. Life and P&C insurers have the lowest variance, while mutual funds that hold short securities have much more variance. Some off-diagonal terms are negative: e.g., the covariance between P&C insurers and long IG mutual funds, while other covariances are positive, such as between long mutual funds and short mutual funds.

Asset-Level Risk Transformation. We transform investor-level risk into asset-level demand-based risk by considering each bond type's exposure to different investor categories. Let S_t be an $C \times N$ matrix where each element $S_{ct}(n) = \frac{paramt_{ct}(n)}{amtout_t(n)}$ represents the share of outstanding bond n held by investor category c, normalized by that investor category's market share. The asset-level variance-covariance matrix of demand risk is then constructed as $\Sigma_{\iota t} = S'_{t-1} \Omega S_{t-1}$, where the subscript notation indicates this is an $N \times N$ matrix.

Principal Component Analysis. We estimate bond-type level demand-based risk (dbr) as the loading on the first principal component of aggregated investor demand shocks. To extract the common demand factor, we proxy the demand shock as $S'_{t-1} \times f^{\perp}$, where S_{t-1} denotes the time-varying matrix that captures, for each quarter, the share of outstanding bond n held by investor category c in the previous period, and $f^{\perp}$ is the constant time-series of weighted-average orthogonalized flows for each investor category. We assume the demand shocks follow a one factor structure:

$$\underbrace{S'_{t-1}}_{N \times C} \times \underbrace{f^{\perp}}_{C \times T} = \alpha + \underbrace{\boldsymbol{\delta}_{t-1}}_{N \times 1} \underbrace{F}_{1 \times T} + u \tag{30}$$

where F represents the first principal component capturing the dominant time-series factor, $\boldsymbol{\delta}_{t-1}$ denotes the corresponding time-varying vector of loadings interpreted as the exposure of each bond type to the common component, and u is the residual matrix. Hence, the asset-level demand shock matrix can be written as $\Sigma_{\iota t} = S'_{t-1}\Omega S_{t-1} = \boldsymbol{\delta}_{t-1}\boldsymbol{\delta}'_{t-1} + \Sigma_{ut}$, where $\boldsymbol{\delta}_{t-1}$ is a $N \times 1$ vector and Σ_{ut} is a diagonal matrix.

The intuition behind our measure is straightforward: we estimate a one-factor model that captures the common component of exogenous investor demand shocks, which we measure using orthogonalized flows. Our estimated factor explains over 80% of the variation in flows, as shown in Figure C.6. Assets that are held by investors whose flows co-move strongly with this factor have higher demand-based risk. When these investors experience correlated outflows, they simultaneously sell similar types of bonds, creating concentrated selling pressure and higher price volatility for those bond types. Firms issuing bonds with higher demand-based risk thus face greater funding uncertainty, as their bond prices become more sensitive to coordinated investor behavior.

Figure 7 reports the time-series trend in asset-level *dbr* across all outstanding bonds in our sample. There has been a slight increase in *dbr* since 2010, potentially corresponding to an increase in mutual funds in the corporate bond market, though the dispersion remains quite large across assets. We further compute the firm-level *dbr* by computing aggregating the *dbr* across a firm's bond portfolio, weighted by total assets. Figure 8 shows how this firm-level *dbr* varies in the cross-section of firms. Larger firms have lower *dbr*, while more levered firms and those with lower credit ratings have higher *dbr*.

4.3.1 Lower demand-based risk, higher prices

Equipped with this asset-level measure of demand-based risk, we test the first part of Hypothesis 3: how *dbr* correlates with prices. We show in Table 7 that *dbr* and relative credit spread are negatively correlated in the cross section, controlling for bond-type level average durations and CDS spreads. Our results also survive rating by month fixed effects and a Fama-MacBeth specification. These results confirm the model prediction that firms face a trade-off between reducing cost of capital and the *dbr* of their bond portfolio, which contributes to their funding risk.

4.3.2 Lower demand-based risk, more issuance

Next, we test if firms actively issue bonds with lower *dbr*, conditional on prices. Ideally, we want to isolate the variation in *dbr* that arises from exogenous changes in asset holding shares, and avoid endogeneity that comes from investors selecting into bond types for unobservable fundamental reasons. Thus, we propose an instrument for *dbr* that exploits variation in asset holding shares s that arise from exogenous flows. The idea here is that if investor portfolio weights are slow-moving, then exogenous flows into investor i in investor group mechanically increase the share s for all n held by investor i, thus increasing exposure to that investor group in a way that is plausibly unrelated to the underlying fundamentals of issuers of that bond type.

$$z_{nt}^{dbr} = \mathbb{1}_n' diag(z_t^{cs'} \Omega z_t^{cs}), \tag{31}$$

where $\mathbb{1}_n$ is a $N \times 1$ vector with all elements equal to 0, except for a 1 in the n-th position, and z_t^{cs} is a $C \times N$ matrix with each element defined as $z_{cnt}^{cs} = \sum_{i \in I_{cnt}} \frac{paramt_{in,t-1}}{amtout_{n,t-1}} \times f_{it}^{SS,\perp}$.

We show in Panel A of Table 5 that the instrument is relevant for demand-based risk. As long as exogenous flows into investors that hold a given bond type are uncorrelated with the firm fundamentals affect issuance decisions, the instrument satisfies the exclusion restriction. We then test whether firms are more likely to issue a new bond type based on variation in relative credit spreads and dbr. Specifically, we run an IV regression with the following second stage:

$$\begin{aligned} issuance_{fnt} = &\gamma_1 \hat{cs}^r_{fn,t-1} + \gamma_2 \hat{dbr}_{n,t-1} + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} \\ &+ \delta_4 DebtDue_{f,t-1} + \delta_5 log(Assets)_{f,t-1} + \alpha_t + \alpha_f + \nu_{fnt} \end{aligned} \tag{32}$$

where we instrument $cs^r_{fn,t-1}$ by $z^{cs}_{n,t-1}$ as before, and instrument $dbr_{n,t-1}$ by $z^{dbr}_{n,t-1}$.

Columns (3) and (4) of of Table 5 show the IV results instrumenting only dbr_{nt}, and columns (5) and (6) show the results instrumenting both cs^r_{fnt} and dbr_{nt}. The coefficient on dbr is negative and significant, indicating that firms are more likely to issue bond types with lower demand-based risk, conditional on instrumented prices. Similarly to the way firms diversify their suppliers of goods to insure against idiosyncratic shocks facing a single supplier, firms will also diversify their supplier of credit in corporate bonds markets to insure against idiosyncratic shocks. The interpretation of coefficient on dbr in specification (5) is: all else equal, a 1 standard deviation decrease in a given bond type's demand-based risk leads to a 0.025 percentage point increase in the firm's issuance to assets ratio for that bond type in that month.[19] This is economically significant and represents about 1% of median quarterly conditional net issuance of a bond type n, or nearly 35% of average unconditional quarterly net issuance.

There is significant heterogeneity across firms in their responsiveness to relative credit spreads and dbr when selecting bonds to issue. Figure F.1 shows that larger firms (as measured by total assets) are more likely to respond to both relative credit spreads and dbr, suggesting financial sophistication is positively correlated with size. Across credit ratings categories, Figure F.2 shows that investment grade firms tend to be more sophisticated than high-yield firms, with A-rated firms more responsive to credit spread while BBB-rated firms are slightly more responsive to dbr.

[19] One standard deviation of the dbr_{nt} is 0.052, the coefficient estimate is 0.035, so $0.48 \times 0.052 = 0.025$.

4.3.3 Robustness: Retail vs. Institutional Flows

We argue that flow-driven price changes for a given bond type influence firms' issuance decisions. To do so, we require that the flows we measure arise from exogenous shifts in demand–stemming from changes in investors' wealth or preferences–rather than from investors anticipating impending supply shocks. Specifically, one might worry that investors direct flows to funds holding bonds of firms with stronger future growth opportunities, thereby anticipating those firms' forthcoming issuances. However, for such behavior to compromise our instrument, it would need to survive our procedure of residualizing flows against contemporaneous returns. That is, investors would need to have private information about firm fundamentals that lead to issuance.

While we find this source of endogeneity unlikely, we can do more to ensure flows are not driven by better-informed investors forecasting future issuance, we differentiate between flows from retail vs. institutional investors. Retail investors are far less likely to possess private information about a firm's fundamentals or its prospective issuance. Thus, if our flows primarily reflected investor anticipation of future supply, one would expect little effect when focusing solely on retail-investor-driven flows. In Table F.3 in the Appendix, we replicate our baseline IV analysis using only flows from retail funds, which make up 31% of the AUM for the mutual funds in our analysis. The qualitative results remain largely unchanged (though magnitudes are somewhat smaller), reinforcing our view that the instrument captures demand-driven variation rather than expectations of future supply.

4.3.4 Robustness: Exposure to Natural Disasters

We further strengthen our results by leveraging variation in insurer holdings driven by property-and-casualty (P&C) insurers' elevated selling around natural disasters, following the methodology and data from Ge and Weisbach (2021) and Ge (2022). First, we construct a measure of unusual weather damage for each state-quarter by taking the dollar amount of weather damages to properties in state s in quarter t, and demeaning this object by its prior average for that state up to time t: $UnusualWeatherDamage_{st} = WeatherDamage_{st} - \overline{WeatherDamage_{st}}$. Next, we allocate these state shocks to each insurer by computing its four-quarter market share of direct premiums in state s: $MktShare_{i,s,q-4\to q-1} = \frac{\sum_{t=q-4}^{q-1} DirectPremium_{i,s,t}}{\sum_{t=q-4}^{q-1}\sum_i DirectPremium_{i,s,t}}$, and then summing the unusual damage across states: $Exposure_{i,q} = \sum_{s\in i} UnusualWeatherDamages_{sq} \times MktShare_{i,s,q-4\to q-1}$. Finally, we translate insurer exposures into bond-type exposures by weighting each insurer i's exposure by its lagged share $w_{i,t-1}(k)$ of bond-type n: $Exposure_{nt} = \sum_{i\in I_{nt}} Exposure_{it} \times w_{i,t-1}(k)$.

Because only a handful of bond types are meaningfully affected by extreme weather, we focus on the ten most exposed bond types and their "neighborhoods", defined as the two adjacent assets in a P&C holding-share ranking across all bond-types. We report the results in Table F.6 in the Appendix. Re-estimating our baseline IV specification on this way yields qualitatively identical findings: a plausibly exogenous negative shock to investor wealth widens credit spreads and dampens net issuance. In addition, weather-driven portfolio rebalancing shifts a bond type's demand-based risk and causes firms to issue less of those bonds whose DBR has increased. The consistency of these results–even within this narrow slice of the market–bolsters our confidence that we are capturing a genuine causal effect in our baseline results.

4.4 Empirical value of firm sophistication

The firm creates value by issuing bonds that are in higher demand if the stock return improves upon issuance. We can test this directly by doing an event study analysis around issuance of a bond type associated with a relative credit spread. To do this, we first construct a firm-specific credit spread variable $cs_{fnt} = \frac{\overline{CS}_{fnt} - \overline{CS}_{ft}}{\overline{CS}_{ft}}$ that captures the firm-specific bond type relative credit spreads, subtracting out any firm-level fluctuations in fundamentals and normalizing by the level of the firm's credit spreads. We then regress the abnormal equity return of a firm's stock on an interaction term of issuance of bond type n and an indicator variable for a lower than usual relative credit spread:

$$\begin{aligned} r^e_{ft} = \beta_0 + \beta_1 \left(\sum_{n\in f} \mathbb{1}[issuance]_{fnt} \times \mathbb{1}[cs_{fn,t-1} < \overline{cs}_{fn,t-1\to t-12}] \right) \\ + \beta_2 GrossIssuance_{ft} + \beta_3 AvgCDS_{ft} + \beta_4 TobinsQ_{ft} + \alpha_f + \epsilon_{ft} \end{aligned} \tag{33}$$

where the abnormal return is computed from the day prior to issuance to the day after issuance minus the market return. We control for firm-level average CDS, Tobin's Q, and issuance size normalized by prior period assets. We run a similar test for *dbr*, constructing a dummy variable for each newly issued bond that equals one if the newly issued bond is of type n with $\mathbb{1}[dbr_{nt} < \overline{dbr}_{f,t-1}]$, that is, a lower *dbr* than the weighted average *dbr* at the firm level in the prior period.

We report results in the first two columns of Table 8, where Panel (a) reports results for relative credit spreads and Panel (b) reports results for *dbr*. Column (2) of Panel (a) shows that, conditional on firm fundamentals, issuing a bond type that is relatively more expensive has a positive impact on the two-day equity return. Netting out the constant term, which represent the effect on stock returns of issuing in general, this effect is 2.7 basis points for the two day window, indicating an approximate annualized abnormal return of 3.5%. This is economically significant but not huge. A similar analysis in columns (3) of Table 8 using the firm's overall enterprise value similarly shows a positive effect; thus the value-add is not simply a transfer from existing debt to equity holders.

We show further that this behavior does not significantly increase the firm's default risk by running a similar event study and replacing the abnormal equity return with the firm-level change in CDS spreads minus the CDX index.[20] Column (4) of Table 8, Panel (a), presents the results. The coefficient on the interaction term of issuance and the relative credit spread is not statistically different from zero. Thus, issuing bonds with a relative credit spread does not increase the default risk of the firm on average.

On the other hand, issuing a bond with a lower *dbr* than the firm's average in the prior period does not have a significant effect on equity returns or enterprise value. Instead, it significantly decreases the firm's CDS upon issuance. These results underscore the credit risk benefit of reducing demand-based risk, while highlighting the trade-off firms face between minimizing their cost of capital and mitigating *dbr*.

[20]Note $\Delta CDS_{ft} = CDS_{f,t+1} - CDS_{f,t-1}$ represents the CDS spread change in the two-day window around issuance in basis points. We use 5-year maturity CDS contracts, as they are they most liquid.

5 Benefits of diversifying funding sources

We have shown that firms prefer to issue bonds with lower demand-based risk, and will even compromise on cost of capital to achieve lower demand based risk. In the model, we posit that firms dislike exposure to funding risk. In this section, we argue why this is the case. We first show that investor demand for certain bond-types is sticky. Consistent with this, firms whose debt is concentrated among a few investors have less price dispersion across their bonds and higher bond return volatility over time. In periods when firms face higher default risk, issuers are thus less able to attract new lenders. In contrast, firms that diversify across bond types–and thus across investor classes–have lower funding risk and tend to be more resilient to credit market shocks.

5.1 Investor demand is insatiable and sticky

We begin by documenting that investors "stick" to the bond types they already favor: when a firm issues additional bonds of type n, those investors with larger pre-issuance holdings of n absorb a disproportionately large share of the new supply. Our model is static and we do not directly observe the hedging demand. We instead proxy this hedging demand by the portfolio weights for each bond type n. Specifically, using bond type by quarter data, conditional on positive net issuance in that bond type, we regress changes in portfolio weight of a given bond type on issuance in that bond type, interacted with the previous portfolio weight that the bond type made up in the investor's portfolio:

$$\Delta\omega_{i,n,t} = \beta_1 issuance_{n,t} + \beta_2 \omega_{i,n,t-1} + \beta_3 issuance_{nt} \times \omega_{i,n,t-1} + \alpha_{i,t} + \epsilon_{i,n,t}, \tag{34}$$

where $\omega_{i,n,t}$ is the change in portfolio weight by fund i of bond type n in period t, normalized by assets under management (AUM) at t, h_{ikt} is the dollar amount that fund i holds of bond type n in period t, and $issuance_{n,t} = \frac{amt_{n,t} - amt_{n,t-1}}{amt_{n,t-1}}$ represents net issuance in period t of bond type n normalized by the total amount outstanding for that bond type n in the previous period.

Results are reported in Table 9. We find that the coefficient on the interaction term, β_3, is positive and statistically significant, showing that investors with higher initial exposure to a bond type purchases disproportionately more when there is new issuance of that bond. The result is robust to fund–quarter fixed effects, which absorb time-varying fund fundamentals, as well as bond type fixed effects. If investors had a pure diversification motive, then we would expect to see $\beta_3 < 0$; that is, the greater the portfolio weight of a bond type in the previous period, the less the fund acquires given new issuance. If, on the other hand, investors had a pure mandate over the portfolio weights of different bond types, we would expect to see $\beta_3 = 0$. Instead, we find that investors that previously held large shares of a given bond type n increased disproportionately their holdings of that bond type following issuance, suggesting their demand for that bond type is insatiable by other assets in the market.

5.2 More concentration in investors reduces price dispersion

For firms to exploit demand-driven price variation, there must be meaningful price dispersion within firm. One way for firms to generate more price dispersion is to issue multiple bond types.[21] By doing so, firms effectively diversify their suppliers of credit. We can test directly how the extent of diversifying the investor base affects price dispersion. To measure investor base diversification, we compute the equivalent of the Herfindahl-Hirschman index for each firm-month based on the shares that each investor holds of the firm's total bond portfolio:

$$HHI_{ft} = \sum_{i \in ft} s_{ift}^2, \tag{35}$$

where $s_{ift} = \frac{\sum_{j \in ift} q_{ijt}}{\sum_{j \in ft} q_{jt}}$ represents the share of firm f's bond portfolio that investor i holds in quarter t.

Next, we run a regression of the within-firm price dispersion on the HHI, where price dispersion $\sigma_{CS,ft}$ is the standard deviation of the firm's credit spreads with firm and quarter fixed effects, and plot a binned scatter plot of the residuals from this regression in Figure 9. As expected, when a firm's investor base is more concentrated (higher HHI), it has lower price dispersion. It is thus less

[21] We show in Appendix C.2 that more bond types corresponds to more price dispersion.

able to exploit the price variation when issuing bonds.

5.3 Higher demand-based risk increases return volatility

We next show evidence that less diversified firms exhibit greater bond-return volatility. To do this, we construct a firm-level measure of diversification across investor shocks, or "demand-based risk". Firm-level demand-based risk is just the aggregation of asset-level demand-based risk at the firm level based on what bonds the firm has outstanding.

A firm's demand-based risk is then computed based on the demand-based risk of the bond types it holds.[22]

$$DemandBased\_Risk_{ft} = \sum_{n \in I_{ft}} \frac{amtout_{fnt}}{assets_{ft}} \times dbr_{nt} \tag{36}$$

First, we find that firms with higher demand-based risk have more return volatility in their bonds. Figure 10 demonstrates that demand-based risk is positively associated with the volatility of the firm's bond portfolio returns (even including firm and time fixed effects), indicating that higher demand-based risk correlates with more volatile bond prices.

5.4 Fewer new lenders in bad times

Why is diversifying credit supply valuable? We showed in Section 2 that investors face demand shocks that are not perfectly correlated. Firms would thus value diversifying across investors only if it is costly to borrow from new investors when they demand capital. If this is the case, then by borrowing from many investors in good times, firms can diversify across these idiosyncratic shocks and maintain credit access when facing a negative shock. In theory, given information asymmetries between firms and investors, investors learn from prices. When corporate bond prices are low, investors cannot fully infer if it is due to bad fundamentals or to a liquidity shock of

[22] This is similar in spirit to the empirical stock fragility in Greenwood and Thesmar (2011) and Friberg et al. (2024).

intermediaries. Thus, intermediaries are more likely to buy bonds from firms that are already within their investment universe, especially in periods of distress (Zhu (2021), Barbosa and Ozdagli (2021)).

Indeed, we find evidence that when a firm issues in a time of distress, as measured by higher CDS prices than usual, it is less likely to have new investors in its bond. To show this, we regress the share of investors that hold a newly issued bond that did not previously lend to the firm ("$share\_new_{ft}$") on the firm's CDS, controlling for the size of the issuance, previous period investment opportunities, and the CDS index, as well as firm and quarter fixed effects.

$$share\_new_{ft} = \beta_1 avgCDS_{f,t} + \beta_2 CDX_t + \beta_3 TobinsQ_{f,t-1} + \beta_4 \frac{issuance_{ft}}{asset_{f,t-1}} + \alpha_t + \alpha_f + \epsilon_{ft} \quad (37)$$

Table 10 shows the results: if a firm issues when its CDS is higher, the share of new investors purchasing its bonds is lower. This indicates that when facing a negative shock, it is more challenging for firms to borrow from new investors. Thus, it is worthwhile for firms to borrow from a wider set of investors in good times, to reduce their funding risk.

Next, we test if access to a wider variety of institutional investors allows firms to better maintain access to capital in times of distress. To this end, we compute a time-varying measure of each firm's resilience by estimating forward-looking betas of a firm's CDS to the CDX index.[23] We interpret the estimated beta coefficient $\hat{\beta}_{f,t,t+5}$ as a measure of resilience: it is the firm's exposure to systematic risk in credit markets. The higher a firm's β, the lower the resilience. We then regress these estimated betas on normalized demand-based risk:

$$\beta^{CDS}_{f,t\rightarrow t+s} = \gamma DBR_{ft} + \delta X_{ft} + \alpha_t + \alpha_f + \varepsilon_{ft} \quad (40)$$

[23] Specifically, we begin at the subsidiary level and compute the issuer-level CDS using the covariance of the issuer CDS and CDX index for the next five years and the variance over the next year, where CDS is calculated from U.S. daily data. See Table 11 for a summary of this and other statistics used in the empirical analysis. Next, we aggregate to firm-month level CDS betas, weighting by the amount outstanding of each subsidiary's bonds from the prior period:

$$\hat{\beta}_{ft} = \sum_{m\in f} w_{mf,t-1}\hat{\beta}_{mft} \quad (38)$$

$$w_{mft} = \frac{amt\_out_{mft}}{amt\_out_{ft}}. \quad (39)$$

where we control for firm (or rating category) fixed effects, investment opportunities, leverage, average CDS, debt coming due, and the number of bond types outstanding.

Table 12 reports the results. We find higher demand-based risk across a firm's bond portfolio corresponds to higher beta to the market CDS in the next five year period. The coefficient on demand-based risk is positive and statistically significant. We interpret this result as follows: firms with lower demand-based risk are less exposed to aggregate risks represented by the CDS index going forward. This correlation is economically significant: specification (4) shows that a one standard deviation decrease in demand-based risk decreases the beta by 0.04, which is 8.6% of the average beta.

In summary, firms benefit from the diversification across investors. Because investor demand is both idiosyncratic and sticky, firms whose debt is concentrated among a few investors have less price dispersion across their bonds and higher bond return volatility over time, leaving them less able to time issuance and thus more exposed to negative shocks. In periods when firms face higher default risk, issuers are less able to attract new lenders. In contrast, firms that diversify across bond types–and thus across investor classes–have lower demand-based risk and tend to be more resilient to credit market shocks.

5.5 Magnitudes

How large is the response of firms to investor demand, quantitatively? We compute some general statistics to approximate an upper bound of the magnitude of this phenomenon. Of the bond issuances in our sample where the firm has multiple bond types to choose from, 73% of newly issued bonds have a lower credit spread at issuance relative to the weighted average credit spread across bond types in the previous month. This is significant, considering that newly issued bonds tend to face a competing force towards a higher credit spread relative to comparable bonds trading in secondary markets. (Cai et al. (2007), Siani (2022)). A simple back of the envelope calculation shows that in the median firm-month, the issuers of these bonds that selected into bond types with lower credit spreads saved 10% of their overall bond interest expense on new issuances.[24]

6 Conclusion

This paper provides empirical evidence that firms strategically respond to segmented investor demands by issuing diverse bond types, trading off between minimizing their cost of capital and diversifying their funding risk. Our findings highlight a market-completion role for firms: by tailoring securities to match heterogeneous investor preferences, firms effectively select their investor base and manage their exposure to investor-specific demand shocks.

We support this interpretation with a theoretical framework in which risk-averse investors, facing short-selling constraints and incomplete hedging opportunities, benefit from firms supplying bonds backed by varied cash flows. Empirical tests confirm our model's key predictions, demonstrating evidence of financially sophisticated firms timing the market to both reduce capital costs and enhance financial resilience through investor diversification. This behavior is value-enhancing for firms.

Our results challenge the traditional Modigliani-Miller perspective, emphasizing instead that in firms integrate investor preferences and diversification considerations in their optimal capital structure decisions. Firms thus behave as financial intermediaries, strategically engineering securities not merely to raise funds but also to ensure sustained market access. This financially sophisticated behavior both enhances firm value and contributes to corporate resilience in the face of aggregate shocks.

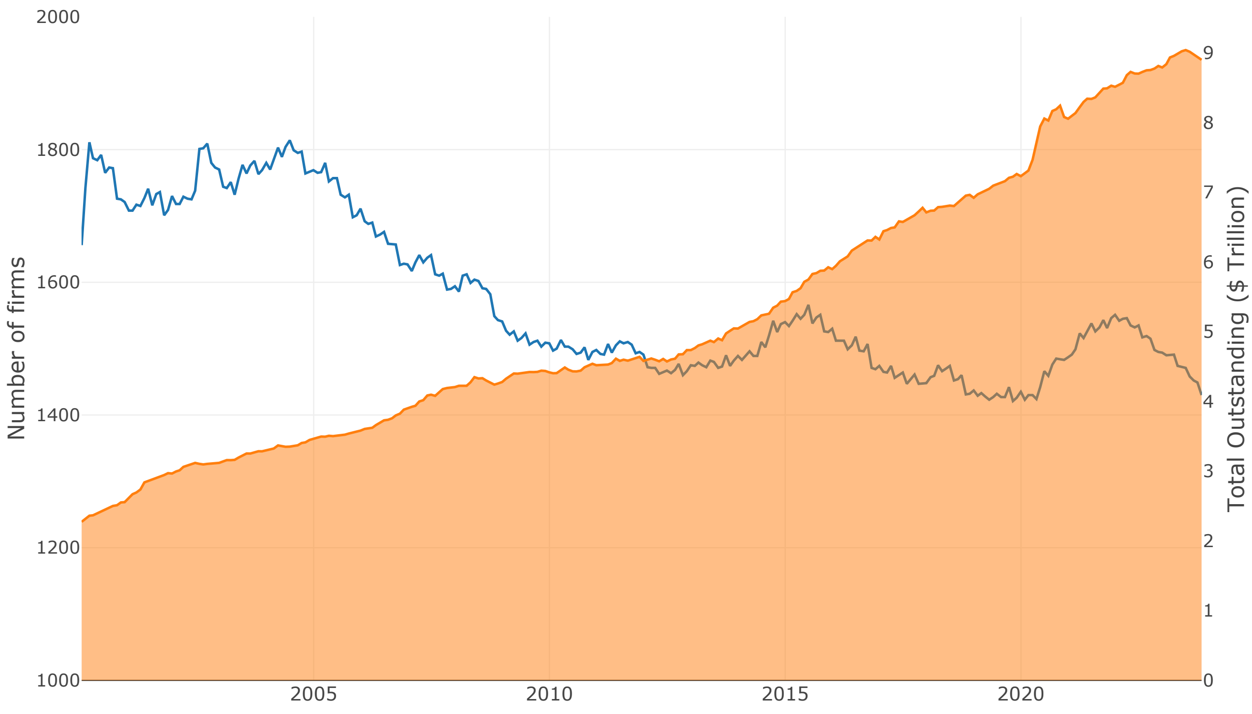
These insights have broad implications for understanding corporate bond market dynamics. Specifically, the frequent issuance of multiple distinct bonds by individual firms to accommodate investor demands may partly explain persistent illiquidity in corporate debt markets (Bao et al. (2011); Goldstein and Hotchkiss (2020)). Exploring the welfare implications of this market segmentation and the broader application of diversification motives to other sources of corporate finance

[24] How do firms know to do this? One possibility is via their underwriter advisors. In Section H in the Appendix, we discuss and show evidence of this channel.

presents promising avenues for future research.

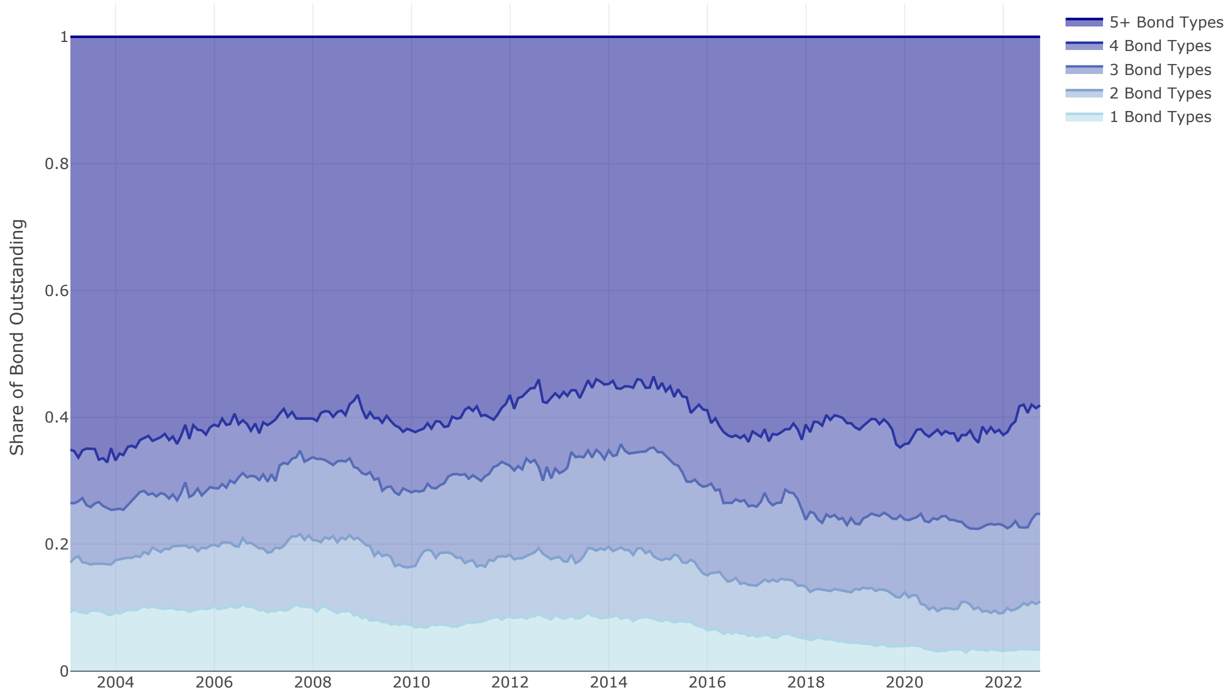
Figures

Figure 1: Bond Issuers and Corporate Bonds Outstanding



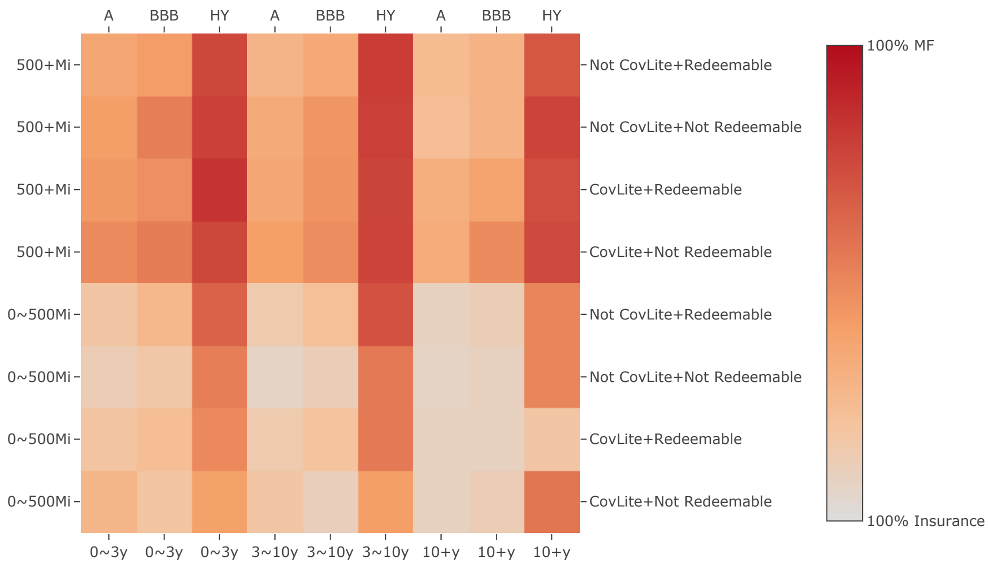
Note: This figure shows the number of U.S. firms with outstanding bonds and the total amount of outstanding corporate bonds over time. The line represents the number of unique firms (*gvkeys*), while the area chart reflects the total bonds outstanding in trillions of U.S. dollas. Data is monthly from January 2000 to October 2023 and computed from Mergent FISD.

Figure 2: One firm can issue many bond types



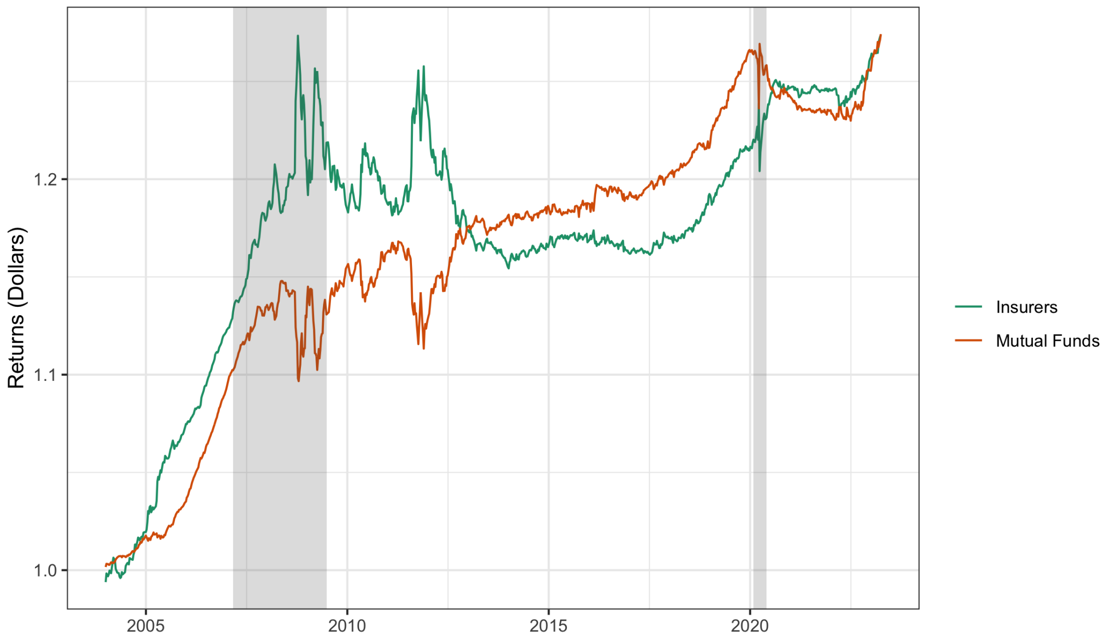
Note: This figure shows the distribution of firms by the number of bond types they issue over time. Bond type is define by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. Data is monthly from January 2003 to December 2023.

Figure 3: Mutual Funds Holdings v.s. Insurer Holdings



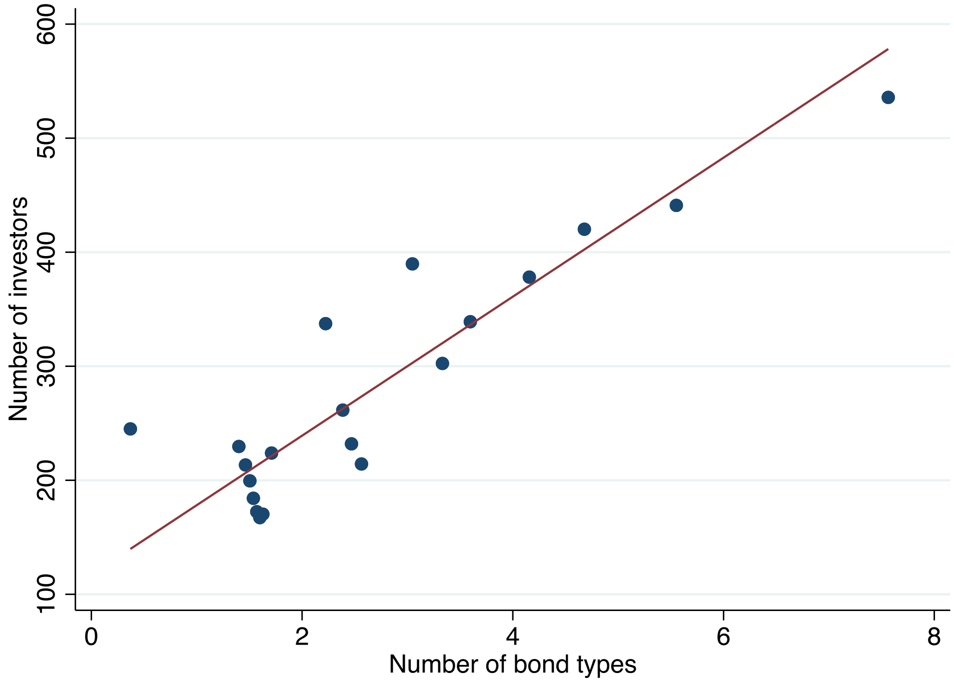
Note: This figure shows the share of amount outstanding held by mutual fund relative to the insurance companies holdings share in a given bond type. Bond type is define by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. We calculate the mutual holdings share from amount outstanding held by mutual funds over total amount outstanding held by mutual funds and insurance companies. Each cube is average mutual fund holdings share across all periods in a given bond type. Data is quarterly from 2003 Q1 to 2022 Q3. We exclude 10 observations where amount of outstanding held by funds is negative, and 0.56% observations where mutual fund holding share or insurers holding share is greater than one.

Figure 4: Long-Short Portfolio Returns



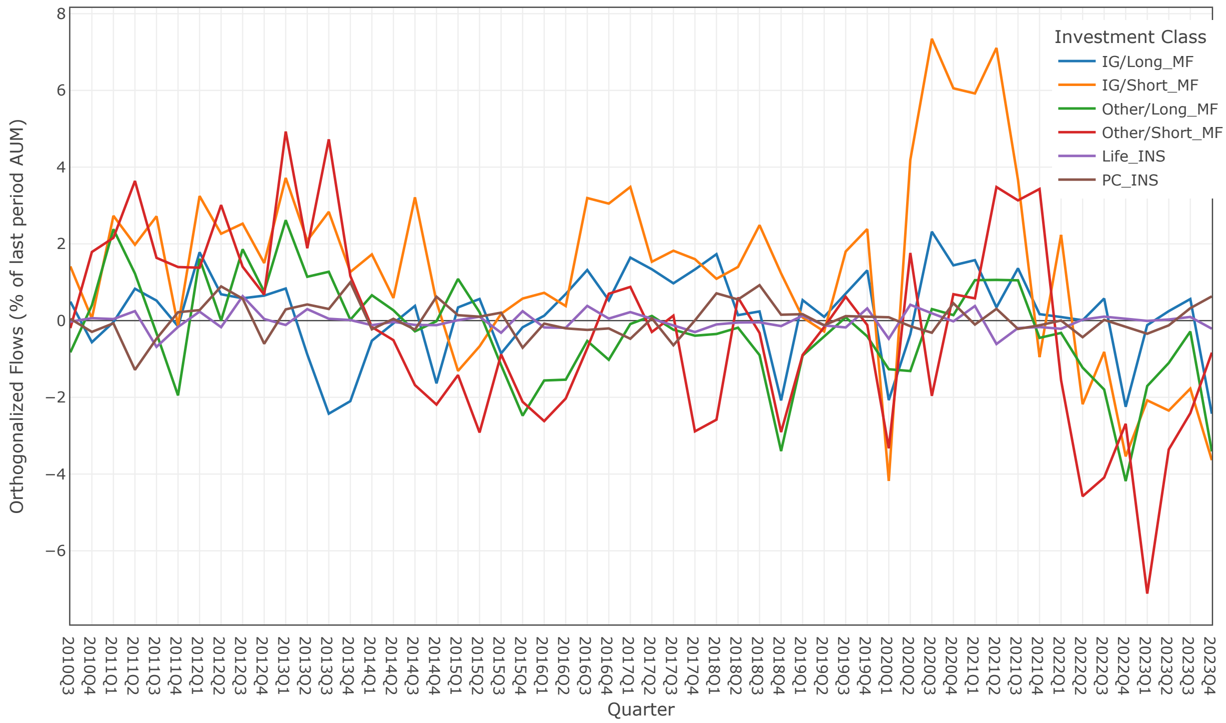
Note: This plot shows the cumulative return for two triple sorted long-short portfolios. The first long-short portfolio is long bonds that are held in high shares by insurers and short bonds that are held in low shares by insurers, within rating and maturity bucket. The second long-short portfolio long bonds that are held in high shares by mutual funds and short bonds that are held in low shares by mutual funds, within rating and maturity bucket. Shaded in gray are recessions defined by the NBER.

Figure 5: Impact of bond type variety on investor heterogeneity



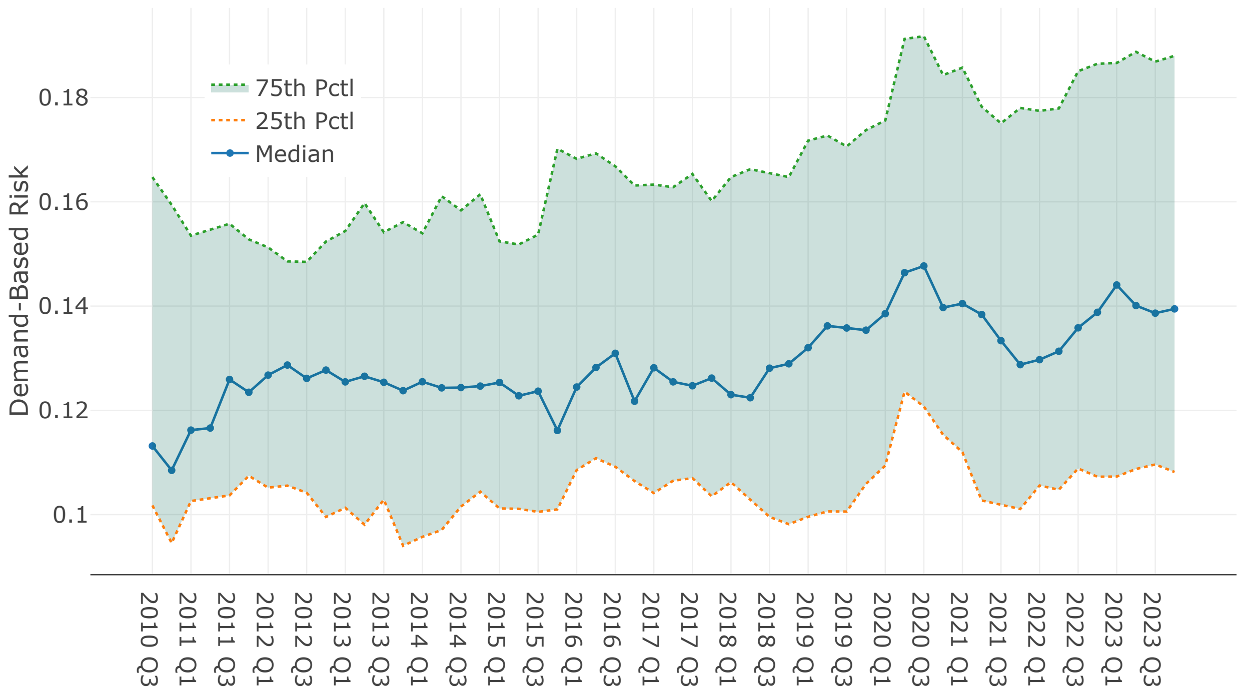
Note: This figure presents how the variety of bond types affect investor heterogeneity across a firm. The y-axis is the number of investors within a firm, while the x-axis is the number of bond types a firm issues. We control for firm's total amount of bonds outstanding and year fixed effects. Bond type is defined by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. Data is quarterly from 2003 Q1 to 2022 Q3 and computed from FISD and eMAXX. We exclude 10 observations where amount of outstanding held by funds is negative and remove 0.56% observations where mutual funds holding share or insurers holding share is greater than one. We winsorize all the variables at 1% and 99% to remove outliers.

Figure 6: Time-series of average orthogonalized flows for each investor category, as % of AUM



Note: This figure shows the time-series of orthogonalized flows for each of the six investor category from 2010 Q3 to 2023 Q4. For each investor category c in quarter t, flows are computed as $f_{ct}^{\perp} = \frac{\sum_{i \in c} f_{it}^{\perp} \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$, where c denotes each of the six investor categories (i.e., IG/Long MFs, IG/Short MFs, HY/Long MFs, HY/Short MFs, Life insurers, and P&C insurers), and $f_{it}^{g} = \beta^{g} R_{it}^{g} + f_{it}^{g,\perp}$, for $g \in$ [Mutual Fund, Life Insurer, P&C Insurer]. Data source: FISD, CRSP for mutual funds, NAIC for insurers.

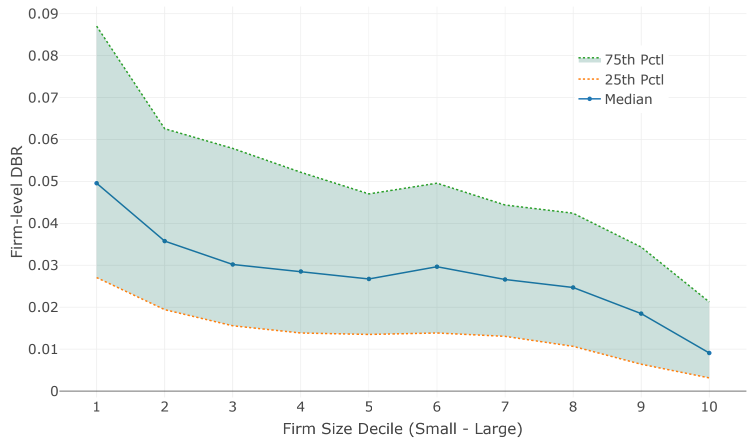
Figure 7: Time-series of demand-based risk



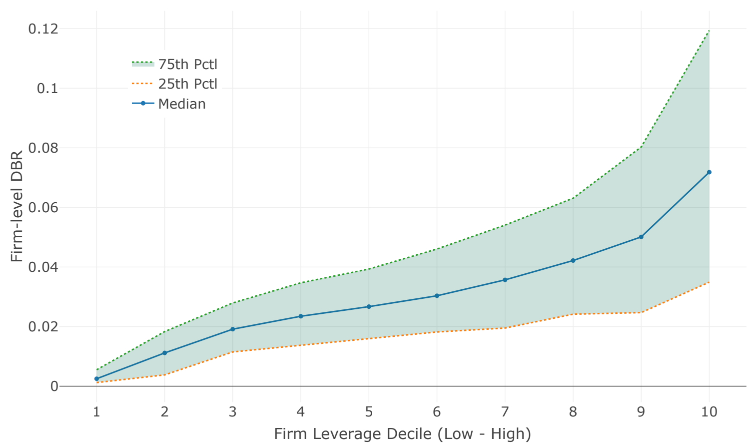
Note: This figure shows the time series of demand-based risk from 2010 Q3 to 2023 Q4. Demand-based risk is constructed as described in Section 4.3. The blue dotted line represents the median demand-based risk, weighted by amount outstanding, while the green shaded area shows the corresponding weighted interquartile range.

Figure 8: Cross-sectional firm-level demand-based risk

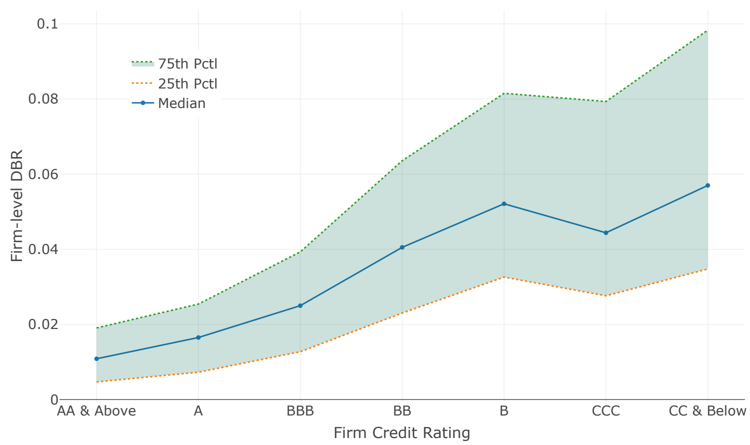
Panel (a): By size deciles



Panel (b): By leverage deciles

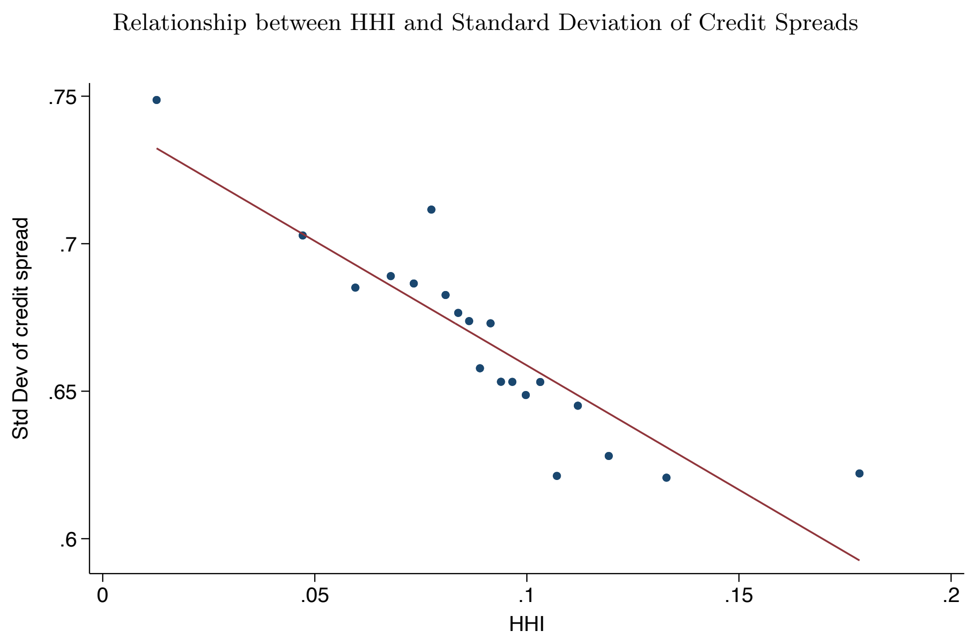


Panel (c): By credit ratings



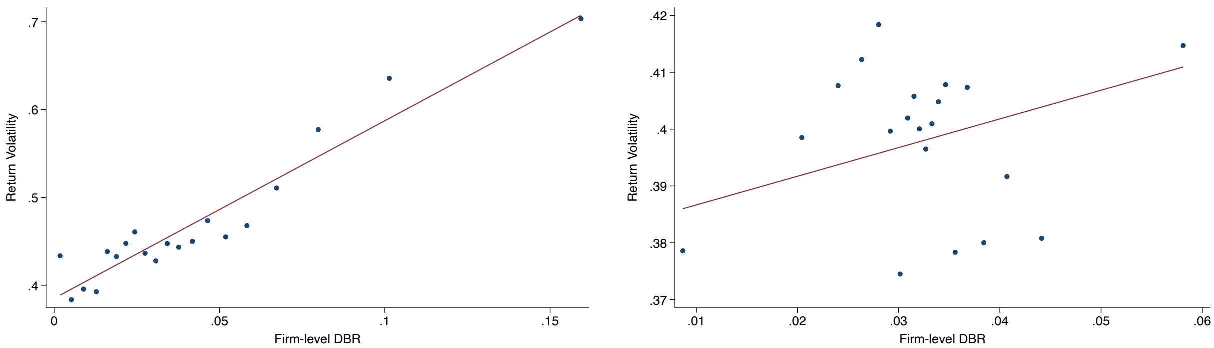
Note: This figure shows the cross-sectional median and interquartile range of firm-level demand-based risk. Panel (a) groups firms by size decile, Panel (b) by leverage decile, and Panel (c) by maximum credit rating. Firm-level demand-based risk is computed as $dbr_{ft} = \sum_{n \in f} \frac{amtout_{fnt}}{ATQ_{ft}} \times dbr_{nt}$. The data sample is quarterly from 2010 Q3 to 2023 Q4.

Figure 9: Impact of bond holding concentration on price dispersion



Note: This figure shows the relationship between HHI and standard deviation of credit spreads. Data is quarterly from 2010 Q3 to 2023 Q4. The HHI is calculated as the sum of squared holding shares across the six investor categories. We control for firm characteristics including Tobin's Q, leverage, average CDS, and debt coming due. Firm fixed effect and quarter fixed effects are included. We winsorize all the variables at 1% and 99% to remove outliers.

Figure 10: Firm demand-based risk and bond portfolio return volatility



(a) Raw data

(b) With fixed effects

Note: This figure presents the relationship between firms' demand-based risk and their volatility of bond-portfolio returns. The x-axis is the year-end firm-level demand-based risk, computed from Equation (36). The y-axis is the firm-year level bond portfolio volatility, defined as: $vol(p)_{ft} = StdDev(\sum_{b \in f} w_{bf,mo-1} r_{b,day})_{ft}$, where $w_{bft} = \frac{amt_{bft}}{amt_{ft}}$ is portfolio weight at firm-bond-month level sourced from FISD, and r_{bt} denotes daily bond returns sourced from iBoxx US. Data is yearly from 2010 to 2023. Firms with fewer than 120 days of valid bond return data per year are excluded. Figure (a) shows the binscatter for raw data; and Figure (b) includes firm and year fixed effects, and firm-level controls (Tobin's Q, leverage, average CDS, debt coming due, log assets). Demand-based risk, price volatility, Tobin's Q, leverage, and debt coming due are winsorized at the 1st and 99th percentiles.

Tables

Table 1: Summary statistics of investor categories

(a) Average fund and bond characteristics by investor category

Investor category	Avg # funds	Avg AUM	Avg flows%	Avg returns	Avg holdings share	Avg maturity	Avg yield
All Investors	842.44	886.14	1.36	0.87	0.12	8.88	4.27
IG/Long MFs	1,119.44	1,026.10	0.50	0.30	0.07	9.90	4.31
IG/Short MFs	296.12	790.55	1.06	0.44	0.04	4.70	3.53
Other/Long MFs	877.45	765.15	0.10	0.78	0.09	9.99	4.43
Other/Short MFs	149.10	391.76	0.82	0.84	0.02	5.13	4.96
PC Insurers	1,648.79	319.69	6.13	0.80	0.06	9.54	4.26
Life Insurers	963.76	1,908.65	0.62	1.14	0.30	9.96	4.33

(b) Average portfolio weight by investor category

	Rating			Remaining Maturity			Size		Covlite		Redemption	
	A	BBB	HY	$<$ 3 years	3 to 10 years	$\geq$ 10 years	$<$ 500 million	$\geq$ 500 million	True	False	Yes	No
All Investors	41.56	39.01	19.44	17.46	54.98	27.57	33.90	66.10	19.91	80.09	81.73	18.27
IG/Long MFs	47.65	42.17	10.18	19.89	53.03	27.08	19.60	80.40	25.51	74.49	76.36	23.64
IG/Short MFs	57.23	39.14	3.63	59.26	40.14	0.60	21.10	78.90	33.61	66.39	65.20	34.80
Other/Long MFs	5.49	15.90	78.61	10.00	76.29	13.71	31.39	68.61	15.86	84.14	90.59	9.41
Other/Short MFs	1.61	8.21	90.18	20.98	77.84	1.17	32.40	67.60	13.03	86.97	92.98	7.02
PC Insurers	56.13	35.76	8.11	25.66	64.23	10.11	32.47	67.53	22.62	77.38	78.75	21.25
Life Insurers	47.70	45.03	7.27	13.84	48.02	38.14	41.79	58.21	17.22	82.78	82.65	17.35

Note: This table presents summary statistics for six investor categories. Panel A shows the average key fund and bond characteristics per investor category, including the average number of funds per quarter, average AUM per fund-quarter, average percentage flows per fund-quarter, average fund portfolio returns per fund-quarter, average share of total bond amount outstanding held per bond-quarter, average time-to-maturity per bond-quarter, and average bond yield per bond-quarter. Panel B shows the portfolio weight of different investor categories across the five dimensions of bond characteristics. Portfolio weight is calculated by dividing the total par value of corporate bonds with a specific bond characteristic within a given investor category by the total par value of all corporate bonds held by that investor category. Each cell represents the average portfolio weight for each investor category across all periods. Data is quarterly from 2003 Q1 to 2023 Q4. Data sources: FISD, eMAXX, CRSP, NAIC, and WRDS Bond Returns.

Table 2: Bond type description

(a) Bond types categorization

Dimension	Buckets	Description
Rating	A	Bonds rated A- or above
	BBB	Bonds rated from BBB- to BBB+
	HY	Bonds rated BB+ or below
Time-to-Maturity	[0y, 3y)	Bonds with a remaining maturity of less than 3 years
	[3y, 10y)	Bonds with a remaining maturity between 3 to 10 years
	[10y, $+\infty$)	Bonds with a remaining maturity of more than 10 years
Size	[0m, 500m)	Bonds with an outstanding amount of less than 500 million
	[500m, $+\infty$)	Bonds with an outstanding amount of larger than 500 million
Covenants	TRUE	Bonds with a number of covenants below the median across all bonds
	FALSE	Bonds with a number of covenants above the median across all bonds
Redemption	YES	Bonds with a redemption option
	NO	Bonds without a redemption option

(b) Bond types consolidation

Bond types before consolidation	Bond types after consolidation
HY_10yy_500mm_TRUE_Y HY_10yy_500mm_TRUE_N HY_10yy_500mm_FALSE_Y HY_10yy_500mm_FALSE_N	HY_10yy_500mm
HY_0y3y_500mm_TRUE_Y HY_0y3y_500mm_TRUE_N HY_0y3y_500mm_FALSE_Y HY_0y3y_500mm_FALSE_N	HY_0y3y_500mm
BBB_10yy_500mm_TRUE_Y BBB_10yy_500mm_TRUE_N BBB_10yy_500mm_FALSE_Y BBB_10yy_500mm_FALSE_Y	BBB_10yy_500mm
HY_3y10y_500mm_TRUE_N HY_3y10y_500mm_FALSE_N	HY_3y10y_500mm_N
A_10yy_500mm_TRUE_N A_10yy_500mm_FALSE_N	A_10yy_500mm_N
BBB_3y10y_500mm_TRUE_N BBB_3y10y_500mm_FALSE_N	BBB_3y10y_500mm_N

Note: This table describes the construction of bond types, which are categorized across five dimensions: rating, remaining maturity, size, covenant-lite, and redemption option. We then consolidate the 72 bond types into 60 merging bond types that consistently have no more than 50 bonds throughout the historical period from 2003 Q1 to 2023 Q4.

Table 3: Summary of firms by number of bond types

	Firms with 1 Bond Type			Firms with multiple Bond Types			Full sample		
# Firms	915			1481			2396		
% A	4.45%			22.37%			16.93%		
% BBB	15.93%			43.26%			34.96%		
% HY	79.63%			34.37%			48.12%		
Bond Characteristics									
	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev
Credit Spread	5.56	4.95	3.38	2.09	1.55	1.99	2.19	1.59	2.13
Time-to-Maturity	5.75	5.42	3.26	10.46	6.83	10.17	10.32	6.75	10.06
Duration	4.28	4.13	1.87	6.71	5.54	4.48	6.64	5.44	4.44
Bond Outstanding (M)	288.41	228.61	228.09	577.34	400	602.73	568.47	400	596.84
Market Cap (M)	286.19	225	232.55	603	421.79	635.13	593.27	413.35	629.01
Firm Characteristics									
	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev
Assets (B)	5.65	1.54	34.27	42.93	9.91	114.63	36.85	7.74	106.67
Market Cap of Equity (B)	2.75	1.01	8.47	25.91	7.43	80.78	22.34	5.47	74.84
Enterprise Value (B)	3.06	1.31	8.53	29.81	9.2	85.19	25.69	6.87	79.02
Number of Investors	64.79	52	54.99	346.8	218	381.22	300.83	168	364.67
Age	18.03	16	12.22	30.9	30	15.81	28.8	27	16
Leverage	0.39	0.39	0.2	0.34	0.33	0.18	0.35	0.33	0.18
Profitability	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Bonds/Debt	0.55	0.51	0.32	0.54	0.55	0.3	0.54	0.55	0.3
Bonds/Asset	0.21	0.18	0.16	0.17	0.16	0.13	0.18	0.16	0.13
Funding Risk	0.48	0.18	2.61	0.32	0.18	0.57	0.35	0.18	1.18
Mutual Funds	0.25	0.23	0.17	0.15	0.11	0.13	0.16	0.12	0.14
Insurance	0.16	0.07	0.21	0.34	0.33	0.21	0.31	0.3	0.22
Pension Funds	0.01	0	0.07	0.01	0	0.02	0.01	0	0.03
Others	0	0	0.01	0	0	0	0	0	0

Note: This table presents summary statistics of firms by number of bond types. Firms with 1 bond type refers to firms that consistently issue only one bond type throughout the whole time period. Conversely, firms with multiple bond types includes those issuing more than one bond types at any time point. We take average credit rating across all bonds within firm as a firm's credit rating within a quarter. % A is share of firms rated A or above; % BBB is share of firms rated BBB; % HY is share of firms rated BB or below. Firm age is defined as the number of years the firm has been listed on Compustat. Profitability is computed from operation profit, scaled by assets. Demand-based risk is defined as Equation (36). The last four rows display the percentage of total bonds outstanding held respectively by different investor categories. Data is quarterly from 2003 Q1 to 2023 Q4. Specifically, we consider only non-financial firms (i.e., those with NAICS3 codes other than 521, 522, or 523) with at least $1 million total assets and book value. Data sources: FISD, Compustat, and eMAXX.

Table 4: Exogenous flows affect relative credit spreads

	$cs^{r}_{fn,t-1}$: Relative credit spread					
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{n,t-1}$: Exogenous net flows	-0.091^{***}	-0.091^{***}	-0.098^{***}	-0.085^{***}	-0.085^{***}	-0.083^{***}
	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.008)
$z^{dbr}_{n,t-1}$				-0.041^{***}	-0.041^{***}	-0.095^{***}
				(0.015)	(0.015)	(0.017)
$Tobin's\ Q_{f,t-1}$		-0.001			-0.001	
		(0.011)			(0.011)	
$Leverage_{f,t-1}$		-0.007			-0.006	
		(0.008)			(0.008)	
$Debt\ coming\ due_{f,t-1}$		-0.030			-0.032	
		(0.046)			(0.046)	
$Average\ CDS_{f,t-1}$		-0.013			-0.009	
		(0.065)			(0.065)	
$Log\ assets_{f,t-1}$		-0.001			-0.001	
		(0.002)			(0.002)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	121.84	20.35	94.58	98.94	99.07	59.92
Observations	133,094	133,094	133,094	133,094	133,094	133,094
R^2	0.050	0.050	0.217	0.050	0.050	0.217
Note:						*p<0.1; **p<0.05; ***p<0.01

This table tests how exogenous flows affect firm's relative credit spreads. The regression panel is at the firm-bond type-quarter level from 2010 Q3 to 2023 Q4. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The outcome variable and independent variable are constructed from Equation (27) and (26). We control for the instrument for demand-based risk for specifications (4) to (6). The firm-level characteristics in specifications (2) and (5) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Standard errors are clustered at the firm level. Data source: FISD, Compustat, WRDS bond return, Markit CDS, eMAXX, and CRSP.

Table 5: How relative credit spreads and demand-based risks affect firms net issuance

Panel A: First stage test for flow-based instruments						
	$cs^r_{fn,t-1}$		$dbr_{n,t-1}$		$cs^r_{fn,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{n,t-1}$: Exogenous net flows	-0.091^{***}	-0.098^{***}			-0.085^{***}	-0.083^{***}
	(0.007)	(0.008)			(0.007)	(0.008)
$z^{dbr}_{n,t-1}$			0.476^{***}	0.559^{***}	-0.041^{***}	-0.095^{***}
			(0.004)	(0.004)	(0.015)	(0.017)
$Tobin's\ Q_{f,t-1}$	-0.001		0.012^{***}		-0.001	
	(0.011)		(0.003)		(0.011)	
$Leverage_{f,t-1}$	-0.007		0.014^{***}		-0.006	
	(0.008)		(0.002)		(0.008)	
$Debt\ coming\ due_{f,t-1}$	-0.030		0.022^{*}		-0.032	
	(0.046)		(0.012)		(0.046)	
$Average\ CDS_{f,t-1}$	-0.013		0.127^{***}		-0.009	
	(0.065)		(0.017)		(0.065)	
$Log\ assets_{f,t-1}$	-0.001		0.004^{***}		-0.001	
	(0.002)		(0.0005)		(0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{fnt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	-0.904^{***}	-0.807^{**}			-1.202^{***}	-1.304^{***}
	(0.321)	(0.324)			(0.376)	(0.431)
$dbr_{n,t-1}$: Demand-based risk			-0.225^{*}	-0.265^{**}	-0.480^{***}	-0.617^{***}
			(0.123)	(0.112)	(0.154)	(0.170)
$Tobin's\ Q_{f,t-1}$	0.069		0.074^{*}		0.075	
	(0.047)		(0.043)		(0.050)	
$Leverage_{f,t-1}$	-0.197^{***}		-0.186^{***}		-0.190^{***}	
	(0.045)		(0.044)		(0.045)	
$Debt\ coming\ due_{f,t-1}$	1.538^{***}		1.571^{***}		1.532^{***}	
	(0.256)		(0.249)		(0.261)	
$Average\ CDS_{f,t-1}$	-0.679^{**}		-0.628^{**}		-0.600^{**}	
	(0.281)		(0.263)		(0.305)	
$Log\ assets_{f,t-1}$	-0.070^{***}		-0.069^{***}		-0.069^{***}	
	(0.010)		(0.011)		(0.010)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	20.35	94.58	290.19	2510.13	99.07	59.92
Observations	133,094	133,094	133,094	133,094	133,094	133,094
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table shows how relative bond-type credit spreads in the previous period would affect the firm's issuance of bond type n in period t. The regression panel is at the firm-bond type-month level from January 2008 to December 2023, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. We include non-financial firms with at least $1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The outcome variable is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's total assets in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize $issuance_{fnt}$, $cs^r_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

Table 6: Covariance matrix of orthogonalized flows

	IG/Long_MF	IG/Short_MF	Other/Long_MF	Other/Short_MF	Life_INS	PC_INS
IG/Long_MF	1.277					
IG/Short_MF	1.443	6.095				
Other/Long_MF	0.628	1.824	1.843			
Other/Short_MF	0.221	3.227	1.983	5.985		
Life_INS	0.061	0.094	0.058	0.017	0.058	
PC_INS	-0.119	-0.005	0.030	0.090	-0.010	0.185

Note: This table shows the covariance matrix Ω within the *demand-based risk* measures. We use the full time series of orthogonalized flows from 2010 Q3 to 2023 Q4 to calculate the covariance matrix of $f^{\perp}_{ct} = \frac{\sum_{i \in c} f^{\perp}_{it} \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$, where c indicates investor category. Investors are categorized into six groups: four groups of mutual funds based on majority of holdings (long IG bonds, short IG bonds, long HY, and short HY), and two groups of insurers based on primary purpose (life insurers and property and casualty insurers. Specifically, IG funds are defined as those where the maximum IG bonds holdings share is at least 95% overtime; otherwise, they are considered as Other funds. Short funds are defined as those in which maximum holdings share in bonds with time to maturity of less then 10 years is 95% or more across time; otherwise, they are considered as Long funds. Data source: WRDS bond return, NAIC, and CRSP.

Table 7: Relationship between demand-based risk and relative credit spread

	cs^r_{nt}: Relative credit spread				
	Panel regression				Fama-MacBeth
	(1)	(2)	(3)	(4)	(5)
dbr_{nt}	-0.152***	-0.158***	-0.180**	-0.143*	
	(0.0557)	(0.0510)	(0.0799)	(0.0803)	
dbr_{nt} (standardized)					-0.0103**
					(0.00465)
$Duration_{nt}$			0.000606	-0.000962	
			(0.00158)	(0.00130)	
$Average\ CDS_{nt}$			0.0238***	0.0462***	
			(0.00591)	(0.00915)	
$Duration_{nt}$ (standardized)					0.00137
					(0.00653)
$Average\ CDS_{nt}$ (standardized)					0.0277***
					(0.00706)
Month FE		✓	✓		
Rating × Month FE				✓	
Observations	9,445	9,445	9,319	9,319	9,319
R-squared	0.001	0.034	0.042	0.128	0.177

Note: This table shows the regression results of cs^r_{nt} on dbr_{nt} using bondtype-month level data from July 2010 to December 2023. Columns (1)-(4) present panel regression estimates, with specifications that vary in the inclusion of time fixed effects and bond-type level controls for weighted-average durations and CDS spreads. Column (5) reports the result of Fama-MacBeth regression, with all independent variables standardized (z-scored). The dependent variable, cs^r_{nt}, is winsorized at the 1st and 99th percentiles. Standard errors are clustered at the time level. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, CRSP, and Markit CDS.

Table 8: Event analysis: Equity and CDS returns upon issuance

Panel (a): Dummy for relative credit spread

	$r^e_{equity,ft}$			$r^e_{enterprise,ft}$		ΔCDS^e_{ft}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_{n \in f} \mathbb{1}[issuance]_{fnt} \times \mathbb{1}[cs_{fn,t-1} < \overline{cs}_{fn,t-1 \to t-12}]$		0.078**	0.082**	0.054**	0.056**	0.0003	0.001
		(0.033)	(0.033)	(0.023)	(0.023)	(0.001)	(0.001)
$Gross\ issuance_{ft}$		1.018	2.995	0.417	2.598*	−0.014	−0.090
		(1.020)	(2.028)	(0.715)	(1.416)	(0.032)	(0.063)
$Tobin's\ Q_{f,t-1}$		−0.013	−0.069***	−0.006	−0.047***	0.001**	−0.001
		(0.012)	(0.024)	(0.009)	(0.017)	(0.0004)	(0.001)
$Average\ CDS_{f,t-1}$		0.018	0.004	0.019	0.017	−0.002***	−0.003***
		(0.023)	(0.028)	(0.016)	(0.020)	(0.001)	(0.001)
Constant	0.001	−0.051		−0.045		0.002	
	(0.016)	(0.040)		(0.028)		(0.001)	
Firm FE			✓		✓		✓
Observations	15,094	15,094	15,094	15,094	15,094	15,094	15,094
R^2	0.000	0.001	0.042	0.0005	0.049	0.001	0.057

Note: *p<0.1; **p<0.05; ***p<0.01

Panel (b): Dummy for demand-based risk

	$r^e_{equity,ft}$			$r^e_{enterprise,ft}$		ΔCDS^e_{ft}	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\sum_{n \in f} \mathbb{1}[issuance]_{fnt} \times \mathbb{1}[dbr_{nt} < \overline{dbr}_{f,t-1}]$		−0.066	−0.041	−0.029	−0.022	−0.005**	−0.005**
		(0.075)	(0.088)	(0.053)	(0.062)	(0.002)	(0.003)
$Gross\ issuance_{ft}$		0.066	2.932**	−0.032	2.186**	0.014	−0.098**
		(0.771)	(1.386)	(0.551)	(0.986)	(0.023)	(0.040)
$Tobin's\ Q_{f,t-1}$		−0.0004	−0.057***	0.002	−0.038***	−0.0003	−0.0004
		(0.009)	(0.019)	(0.007)	(0.013)	(0.0003)	(0.001)
$Average\ CDS_{f,t-1}$		−0.044**	−0.035	−0.017	−0.002	−0.006***	−0.005***
		(0.021)	(0.027)	(0.015)	(0.019)	(0.001)	(0.001)
Constant	0.003	0.108		0.042		0.009***	
	(0.015)	(0.082)		(0.059)		(0.002)	
Firm FE			✓		✓		✓
Observations	15,216	15,216	15,216	15,216	15,216	15,216	15,216
R^2	0.000	0.0003	0.046	0.0001	0.055	0.006	0.069

Note: *p<0.1; **p<0.05; ***p<0.01

Note: This table examines how a firm's increased issuance of a given bond type n at time t, in response to the relative credit spread and demand-based risk of that bond type, affects its equity, enterprise, and CDS returns. The sample includes firms' new issuance events from January 2004 to December 2023. The outcome variables are the firm's equity return relative to the market return in columns (1)-(4), firm's weighted enterprise return relative to the market return in columns (4)-(5), and the change in CDS spread relative to the CDX in columns (6)-(7), all in percentage points, from period $t-1$ to $t+1$, where t is the event date of firm f issuing bond type n. $\mathbb{1}[issuance]_{fnt}$ is a dummy variable indicating whether firm f issues bond type n on date t. The key independent variable is the sum of the products of the issuance dummy and the CS (DBR) dummy across all bond types issued by firm f, with a maximum possible value of 1. All continuous variables are winsorized at the 1st and 99th percentiles.

Table 9: Impact of prior holdings on holdings change after issuance

	$\Delta\omega_{ikt}$: Portfolio Weights Change		
	(1)	(2)	(3)
$issuance_{kt} \times \omega_{ikt-1}$	0.165***	0.162***	0.186***
	(0.001)	(0.001)	(0.001)
$issuance_{kt}$	0.002***	0.002***	0.002***
	(0.00001)	(0.00001)	(0.00001)
ω_{ikt-1}	−0.011***	−0.031***	−0.002***
	(0.0001)	(0.0002)	(0.0001)
Fund FE	Yes	Yes	No
Quarter FE	Yes	Yes	No
Fund × Quarter FE	No	No	Yes
Bond Type FE	No	Yes	Yes
Observations	6,506,760	6,506,760	6,506,760
R^2	0.113	0.131	0.414
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: This table presents regression results of how the prior fund holdings affect the subsequent holdings changes for a specific bond type conditioning on positive net issuance. Bond type is define by bond characteristics including rating, remaining maturity, size, covenant lite, and redemption. i, k, t refer to fund, bond type, quarter, respectively. The dependent variable $\Delta\omega_{i,n,t}$ is the fund portfolio weights change in a specific bond type n at quarter t. $\omega_{i,n,t}$ is computed from the fund holdings in a specific bond type i scaled by the fund asset under management (AUM) at quarter t. The independent variable of interest is the interaction of $issuance_{n,t}$ and $\omega_{i,n,t-1}$. $issuance_{n,t}$ is the total amount of outstanding changes at quarter t normalized by total amount of outstanding at quarter $t-1$ in a specific bond type n. Data is quarterly from 2003 Q1 to 2022 Q4 and computed from FISD and eMAXX. We exclude 0.01% short term bonds with offering maturity ≤ 1 year. We remove 10 observations where amount of outstanding held by funds is negative and 2.2% observations where mutual funds holdings share or insurers holdings share is greater than one. We winsorize all variables at 1% and 99% to remove outliers.

Table 10: Impact of negative shocks on investor heterogeneity within a firm

	$share\_new_{ft}$			
	(1)	(2)	(3)	(4)
Average CDS	-1.169^{***}	-2.198^{***}	-0.967^{**}	-1.227^{**}
	(0.309)	(0.306)	(0.464)	(0.518)
CDX	-308.177^{***}			
	(84.305)			
Normalized issuance	168.936^{***}	169.316^{***}	172.822^{***}	116.396^{***}
	(6.716)	(6.269)	(6.338)	(7.458)
Tobin's Q in previous period	-0.245^{***}	-0.110^{*}	-0.129^{**}	-0.221^{***}
	(0.066)	(0.062)	(0.062)	(0.079)
Average CS in previous period			-1.404^{***}	0.619
			(0.399)	(0.440)
Constant	45.162^{***}			
	(0.578)			
Quarter FE	No	Yes	Yes	Yes
Firm FE	No	No	No	Yes
Observations	4,050	4,050	4,050	4,050
R^2	0.140	0.281	0.284	0.640
Note:		*p<0.1; **p<0.05; ***p<0.01		

Note: This table shows how the negative shocks affect the investor heterogeneity within a firm at issuance. The sample includes firms' new issues events from 2003 Q1 to 2021 Q4. The outcome variable $share\_new_{ft}$ is the fraction of number of new investors holding the newly issued bonds. We define new investors as fund that holds the newly issued bond from a certain firm but has no prior holdings of bonds from that firm, or fund that has held a bond from a given firm before but did not hold one in the quarter prior to issuance. Data are quarterly and calculated from Markit CDS, FISD, Compustat, and WRDS bond return. We winsorize all the variables at 1% and 99% to remove outliers.

Table 11: Descriptive statistics of key variables

Panel A: Unconditional full sample								
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
$issuance_{fnt}$	133,094	0.072	0.540	−1.155	0.000	0.000	0.000	4.129
$cs^r_{fn,t-1}$	133,094	0.004	0.168	−0.686	−0.053	0.006	0.062	0.662
$z^{cs}_{n,t-1}$	133,094	0.044	0.079	−0.333	0.0004	0.039	0.086	0.484
$dbr_{n,t-1}$	133,094	0.119	0.052	0.009	0.079	0.109	0.153	0.299
$z^{dbr}_{n,t-1}$	133,094	0.021	0.035	0.00002	0.002	0.007	0.024	0.202
$DBR_{f,t-1}$	132,955	0.032	0.030	0.000	0.016	0.027	0.041	0.964
$Tobin's\ Q_{f,t-1}$	133,094	0.042	0.066	0.005	0.015	0.024	0.041	0.505
$Leverage_{f,t-1}$	133,094	0.336	0.146	0.029	0.236	0.336	0.436	0.695
$Average\ CDS_{f,t-1}$	133,094	0.014	0.013	0.001	0.006	0.009	0.015	0.093
$Debt\ coming\ due_{f,t-1}$	133,094	0.006	0.011	0.000	0.000	0.000	0.007	0.057
$Log(assets)_{f,t-1}$	133,094	10.412	1.258	4.190	9.574	10.396	11.195	13.856
β^{CDS}	53,526	0.460	0.608	−0.933	0.068	0.301	0.626	12.879
Panel B: Conditional on positive issuance								
$issuance_{fnt}$	5,448	2.167	1.468	0.033	0.828	1.847	4.068	4.129
$cs^r_{fn,t-1}$	5,448	0.001	0.124	−0.404	−0.054	0.006	0.058	0.442
$z^{cs}_{n,t-1}$	5,448	0.055	0.086	−0.333	0.005	0.050	0.102	0.484
$dbr_{n,t-1}$	5,448	0.120	0.051	0.024	0.085	0.106	0.146	0.297
$z^{dbr}_{n,t-1}$	5,448	0.022	0.035	0.00002	0.002	0.008	0.025	0.202
$DBR_{f,t-1}$	5,446	0.033	0.029	0.000	0.016	0.026	0.041	0.762
$Tobin's\ Q_{f,t-1}$	5,448	0.045	0.071	0.005	0.016	0.024	0.044	0.505
$Leverage_{f,t-1}$	5,448	0.343	0.146	0.029	0.245	0.350	0.435	0.695
$Average\ CDS_{f,t-1}$	5,448	0.012	0.012	0.001	0.005	0.008	0.013	0.090
$Debt\ coming\ due_{f,t-1}$	5,448	0.008	0.012	0.000	0.000	0.00000	0.011	0.057
$Log(assets)_{f,t-1}$	5,448	10.581	1.245	7.108	9.707	10.561	11.424	13.773
β^{CDS}	2,448	0.438	0.569	−0.798	0.067	0.278	0.595	12.879

Note: This table shows the descriptive statistics for key variables. Panel A shows the summary statistics across full sample of Table 5, and the Panel B is conditional on the positive $issuance_{fnt}$. $issuance_{fnt}$ is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's total asset in the prior periods. ζ_{fnt} and instrumental variable κ_{nt} are constructed from Equation (27). demand-based risk is calculated from Equation (36). $\beta^{CDS}_{f,t\rightarrow t+s}$ is a time-varying measure of firm's resilience from 2010 Q3 to 2018 Q4, which is constructed from Equation (38). The regression panel is at the firm-bond type-quarter level, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. The sample spans 2010 Q3 to 2023 Q4 and includes non-financial firms with at least $1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. We winsorize $issuance_{fnt}$, $cs^r_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles.

Table 12: Impact of firm's demand-based risk on credit betas

	$\beta^{CDS}_{f,t\to t+s}$			
	(1)	(2)	(3)	(4)
DBR_{ft}	1.811***	1.284***	4.687***	1.313***
	(0.294)	(0.378)	(0.379)	(0.447)
$Tobin's\ Q_{ft}$			−0.0004	0.0003
			(0.001)	(0.001)
$Leverage_{ft}$			0.093**	−0.220***
			(0.039)	(0.070)
$Average\ CDS_{ft}$			0.178***	0.083***
			(0.007)	(0.007)
$Debt\ coming\ due_{ft}$			−0.491	0.068
			(0.363)	(0.243)
$Log\ assets_{ft}$			0.122***	0.135***
			(0.004)	(0.016)
Firm FE		✓		✓
Rating FE	✓		✓	
Time FE	✓	✓	✓	✓
Observations	20,822	20,822	20,822	20,822
R^2	0.114	0.694	0.190	0.697
Note:		*p<0.1; **p<0.05; ***p<0.01		

Note: This table shows the estimates of how firm's demand-based risk would affect its resilience to negative shocks. The sample period is monthly from July 2010 to December 2018. The independent variable is computed from Equation (36). The outcome variable is a time-varying measure of firm's resilience, which is constructed from Equation (38) and converted to quarterly data by taking the last records in each quarter. The firm-level controls include Tobin's Q, leverage, average CDS spread, debt coming due, log assets, and number of bond types in period t (start date of the five-year rolling window). Demand-based risk, Tobin's Q, leverage, and debt coming due are winsorized at 1st and 99th percentiles. Data source: Markit CDS, Compustat, FISD, NAIC, CRSP, and eMAXX.

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A Notation

We notate bond types as $n = 1, 2, \ldots, N$, individual investors as $i = 1, \ldots, I$, investor categories as $c = 1, \ldots, C$, and factors as $k = 1, \ldots, K$.

B Merge method

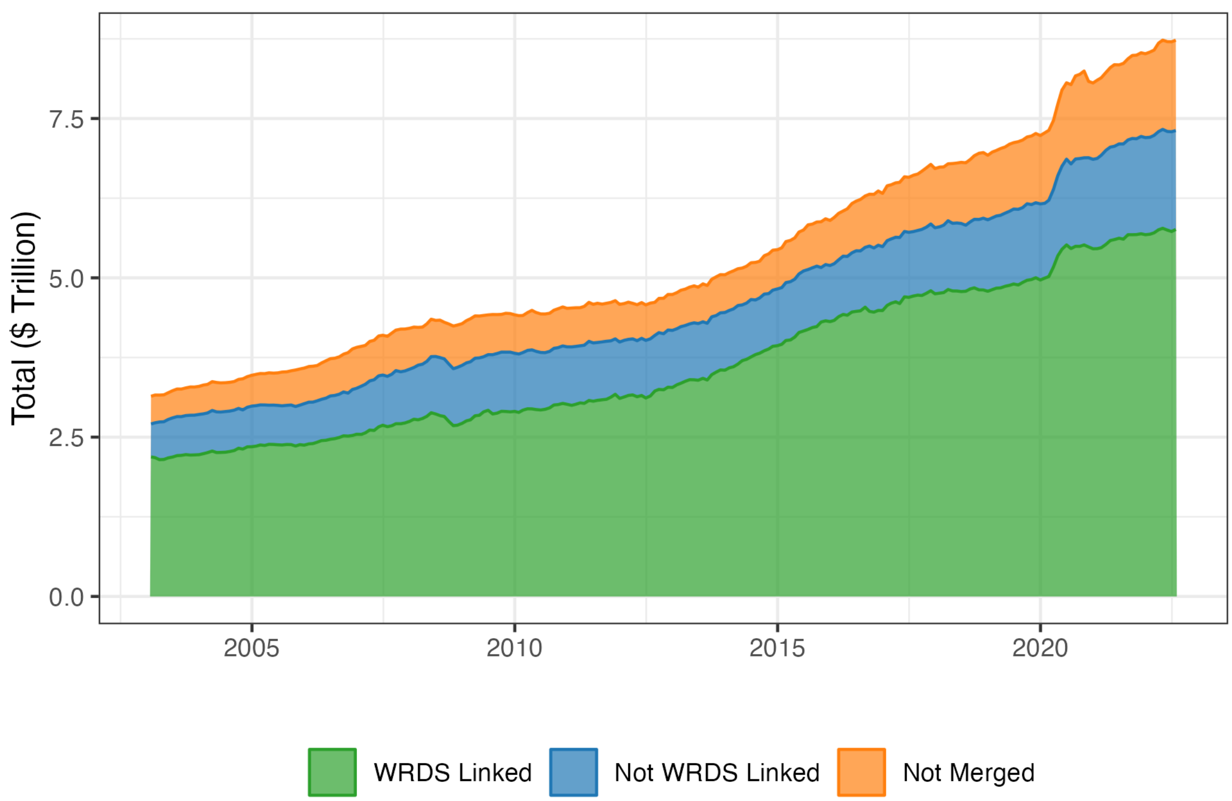
The main goal for the merge between FISD and Compustat was to add the gvkeys found in Compustat to the FISD data. The linked table should be issuer centered, i.e., each bond issuer entity should be linked only to one GVKEY at a point in time. Because each parent company, represented by the GVKEY, might have many issuer subsidiaries, one GVKEY might be linked to multiple issuers at the same time. We start with several cleaning steps: (1) considering only corporate bonds, (2) looking at only dollar-denominated bonds, and (3) analyzing only by industry, while excluding specific sectors like government and hospitals.

Bond characteristics are provided by FISD, this includes issue and issuer identifiers, issuer's cusips, and amount outstanding. Our sources to link issuer identifiers to GVKEYS in hierarchical order of usage are: the WRDS bond returns link tables, S&P Ratings names tables that containing information on parent companies, historical CUSIPs in CRSP in stock names, and CUSIPS from Compustat names table. Next, we use CRSP and Compustat historical legal names, to string match company names with the issuer name in the bond prospectus. Finally, we use the WRDS relationships table to group together gvkeys that file SEC filings as a group and assign them all a parent gvkey to account for conglomerates that have one publicly traded holding company and many wholly-owned private subsidiaries that issue debt. After all the steps we do myriad of manual checks. The manual checks are important to fix wrong merges specially from the WRDS link, cusips and string match, and to deal with duplicates.

Figure B.1 the share of the total amount outstanding of corporate bonds merged using only the WRDS bond returns link table and our extra merge. As the end of 2022, WRDS link was able to successfully link 66% of the almost \$9 trillion of bonds outstanding. Our final merge covers instead 82% of the total amount outstanding.

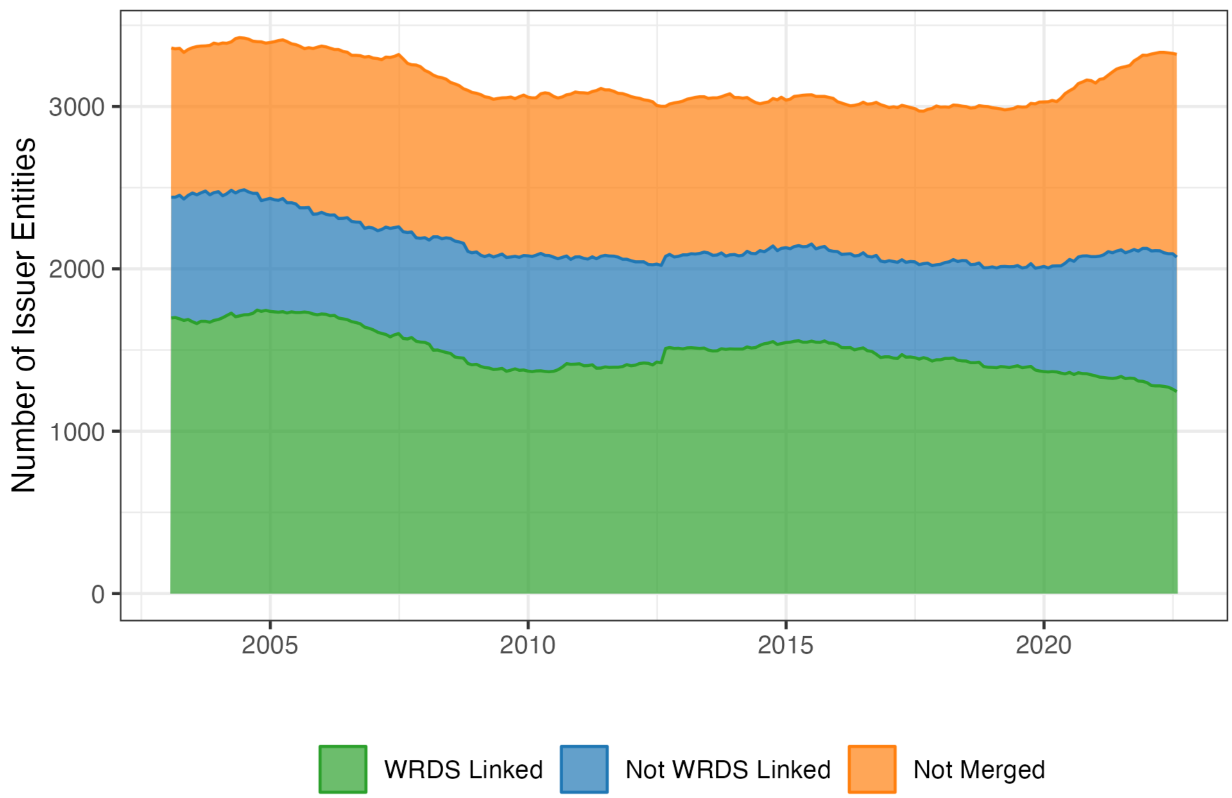
Because WRDS link is more likely to miss on smaller issuer, which many times are subsidiaries of rather than parent companies, it is also interesting to check the number of bond issuers in our final data. The summary is plotted in Figure B.2. As end of 2022, out of the 3321 issuers in the data, 1244 or 37% is merged to a valid GVKEY using WRDS link. We are able to merge an extra 828 issuers, improving the merge to add by an extra 25% of firms. There are still an astonishing 1249 or 38% that are not merged. With our manual check, we noticed that large portion of the cases are international firms that issue US dollar denominated bonds through US subsidiaries. These firms are not covered in the Compustat North America. There are still issuer companies that we fail to merge, but we are currently working with a team of RAs to improve on this merge.

Figure B.1: Total Corporate Bonds Amount Outstanding Merged with Compustat



Note: This figure shows the amount outstanding of all corporate bonds for which we are able to assign a valid GVKEY using only the WRDS link table, the amount we are able to merge using alternative methods, and the amount the remains unmerged. That covers US dollar denominated bonds.

Figure B.2: Total Number of Corporate Bonds Issuer Entities Merged with Compustat



Note: This figure shows the number of issuers of corporate bonds for which we are able to assign a valid GVKEY using only the WRDS link table, the number we are able to merge using alternative methods, and the number that remains unmerged. That covers US dollar denominated bonds.

C Definition of bond type

C.1 Classification and consolidation of bond types

In an attempt to quantify the heterogeneity of bond structure in a tractable way, we construct a measure of unique bond type based on five dimensions: credit rating, time to maturity, issuance size, covenants, and redemption option. There should be 72 unique bond types in total based on our specifications. However, some bond types consistently have no more than 50 unique bonds outstanding in each period of our sample. We then consolidate 18 of these bond types into 6 broader categories, resulting in 60 unique bond types in our final sample. Table C.1 presents the distribution of number of unique corporate bonds in each bond type.

Table C.1: Summary of bond types

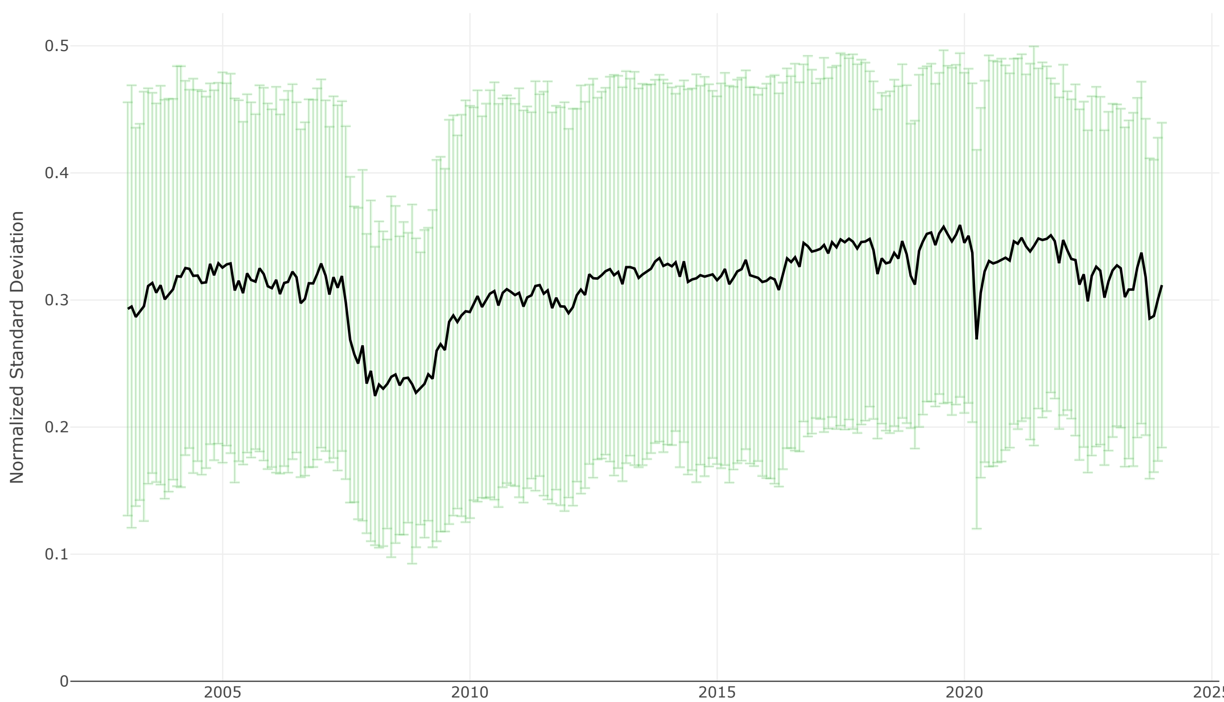
	bond_type_id	Average # bonds	10th Percentile	Median	90th Percentile
1	HY_0y3y_0m500m_TRUE_N	3,999	233	2,542	11,309
2	HY_0y3y_0m500m_TRUE_Y	2,468	77	500	7,992
3	A_0y3y_0m500m_TRUE_N	1,981	458	1,248	4,145
4	HY_3y10y_0m500m_TRUE_N	1,678	218	700	4,636
5	HY_3y10y_0m500m_TRUE_Y	1,527	383	545	4,740
6	HY_3y10y_0m500m_FALSE_Y	1,047	723	907	1,548
7	A_3y10y_0m500m_TRUE_N	1,035	670	966	1,428
8	BBB_3y10y_0m500m_FALSE_Y	690	591	706	746
9	A_10yy_0m500m_TRUE_Y	604	459	582	754
10	BBB_3y10y_500mm_FALSE_Y	526	183	399	1,156
11	A_3y10y_0m500m_TRUE_Y	509	286	404	988
12	A_10yy_0m500m_FALSE_Y	499	336	504	664
13	BBB_10yy_0m500m_FALSE_Y	477	413	456	599
14	HY_3y10y_500mm_FALSE_Y	418	162	378	751
15	A_3y10y_500mm_FALSE_Y	397	149	378	668
16	BBB_10yy_500mm	379	131	250	862
17	HY_0y3y_0m500m_FALSE_Y	356	246	358	470
18	A_10yy_0m500m_TRUE_N	347	213	375	452
19	BBB_3y10y_0m500m_TRUE_N	337	176	284	558
20	BBB_0y3y_0m500m_TRUE_N	332	158	237	702
21	A_10yy_500mm_FALSE_Y	323	80	244	710
22	A_3y10y_0m500m_FALSE_Y	319	277	320	357
23	BBB_0y3y_0m500m_FALSE_Y	312	186	344	396
24	HY_10yy_0m500m_FALSE_Y	269	147	222	442
25	HY_10yy_0m500m_TRUE_Y	255	111	255	402
26	A_0y3y_500mm_TRUE_N	236	131	220	381
27	BBB_3y10y_0m500m_TRUE_Y	235	135	165	454
28	A_0y3y_0m500m_TRUE_Y	214	107	170	283
29	BBB_10yy_0m500m_TRUE_Y	202	103	136	379
30	A_0y3y_0m500m_FALSE_N	197	43	78	582
31	A_3y10y_0m500m_FALSE_N	188	62	98	533
32	BBB_0y3y_500mm_FALSE_Y	188	26	111	436
33	A_0y3y_500mm_FALSE_Y	182	16	208	323
34	HY_10yy_0m500m_TRUE_N	171	88	165	284
35	A_0y3y_0m500m_FALSE_Y	163	90	173	221
36	A_10yy_0m500m_FALSE_N	158	29	167	277
37	HY_3y10y_0m500m_FALSE_N	154	113	149	200
38	HY_0y3y_0m500m_FALSE_N	145	109	140	191
39	BBB_3y10y_0m500m_FALSE_N	144	70	118	280
40	BBB_10yy_0m500m_TRUE_N	140	94	136	188
41	A_3y10y_500mm_TRUE_N	134	64	130	241
42	HY_3y10y_500mm_TRUE_Y	134	20	148	233
43	BBB_10yy_0m500m_FALSE_N	133	46	142	215
44	HY_0y3y_500mm	130	24	121	230
45	BBB_0y3y_0m500m_FALSE_N	130	62	79	292
46	A_3y10y_500mm_TRUE_Y	124	23	96	252
47	BBB_0y3y_0m500m_TRUE_Y	102	49	76	181
48	HY_10yy_500mm	87	48	88	115
49	A_0y3y_500mm_TRUE_Y	86	3	46	217
50	A_0y3y_500mm_FALSE_N	81	26	80	132
51	BBB_3y10y_500mm_TRUE_Y	79	17	45	186
52	A_10yy_500mm_TRUE_Y	73	23	54	164
53	A_3y10y_500mm_FALSE_N	68	8	68	124
54	HY_10yy_0m500m_FALSE_N	56	17	56	94
55	BBB_3y10y_500mm_N	53	31	53	75
56	HY_3y10y_500mm_N	52	28	42	91
57	A_10yy_500mm_N	44	29	46	55
58	BBB_0y3y_500mm_TRUE_Y	37	2	12	106
59	BBB_0y3y_500mm_FALSE_N	36	16	31	59
60	BBB_0y3y_500mm_TRUE_N	30	11	30	53

Note: This table shows the distribution of number of unique corporate bonds outstanding in each bond type in the FISD data. There are five dimensions in the bond type: (1) Rating buckets: HY refers to bonds rated BB or below, BBB to bonds rated BBB, and A to bonds rated A or above; (2) Remaining maturity: the difference between the bond's maturity date and the report date; (3) Size bucket: whether the bond's outstanding amount exceeds $500 million; (4) Covenant-lite: TRUE indicates that the bond has fewer covenants than the median number across all bonds during the period; (5) whether the bond has a redemption option (Y) or not (N). We consolidate 18 of bond types that consistently have no more than 50 bonds, resulting in 60 unique bond types in the final data.

C.2 Bond types and pice variation

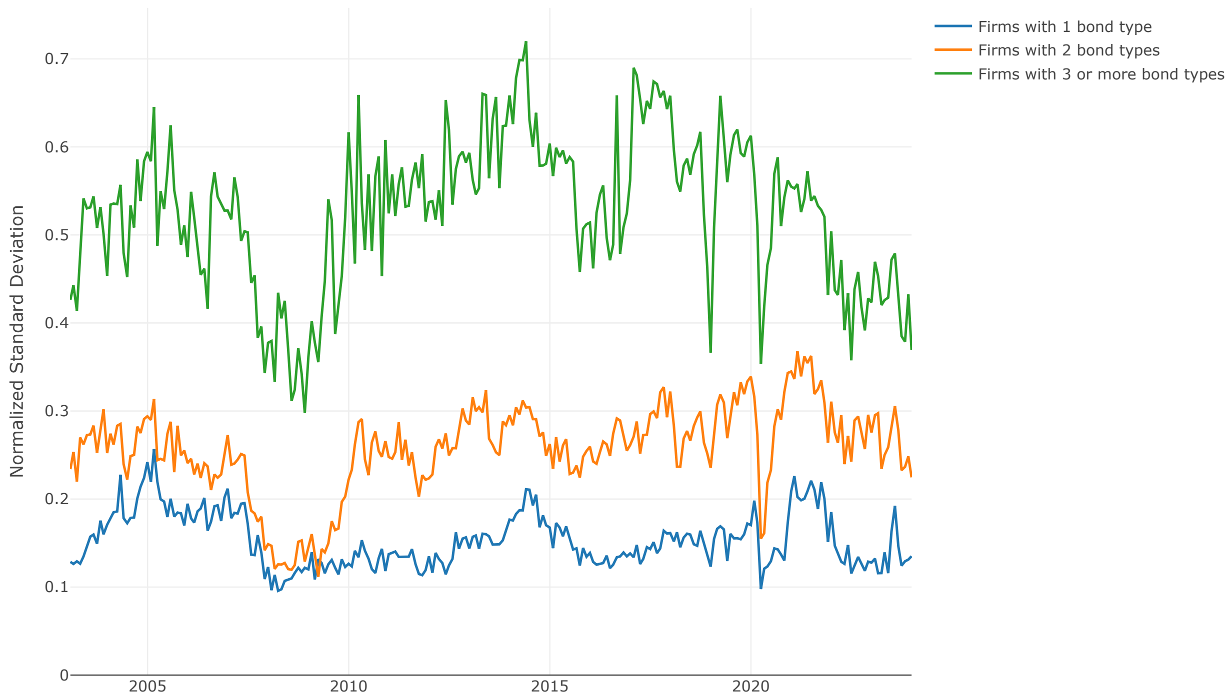
Differing bond types can also help explain within-firm price dispersion. To show this, we first compute a metric for price dispersion, $\sigma_{CS,ft}$, which is the standard deviation of credit spreads across all bonds that a firm has outstanding in a given month. We plot the weighted average of this metric in the cross-section of firms over time in Figure C.1, with bars representing the interquartile range. To ensure this pattern is not being driven by time-series variation in average levels of credit spreads (Gilchrist and Zakrajšek (2012)), we normalize our metric of price dispersion by the average credit spread level for that firm-month. The price dispersion is consistently greater than zero, equal to about 30% of the average credit spreads. Moreover, price dispersion is higher for firms with multiple bond types. Figure C.2 compares the time series of price dispersion for bonds that have only one bond type outstanding to those with two bond types to those with three or more bond types, showing a clear monotonic relationship.

Figure C.1: Normalized Price Dispersion Overtime with Interquartile Range



Note: This figure shows the interquartile range of face-valued weighted normalized standard deviation of credit spread within a firm. Data is monthly from January 2003 to December 2023.

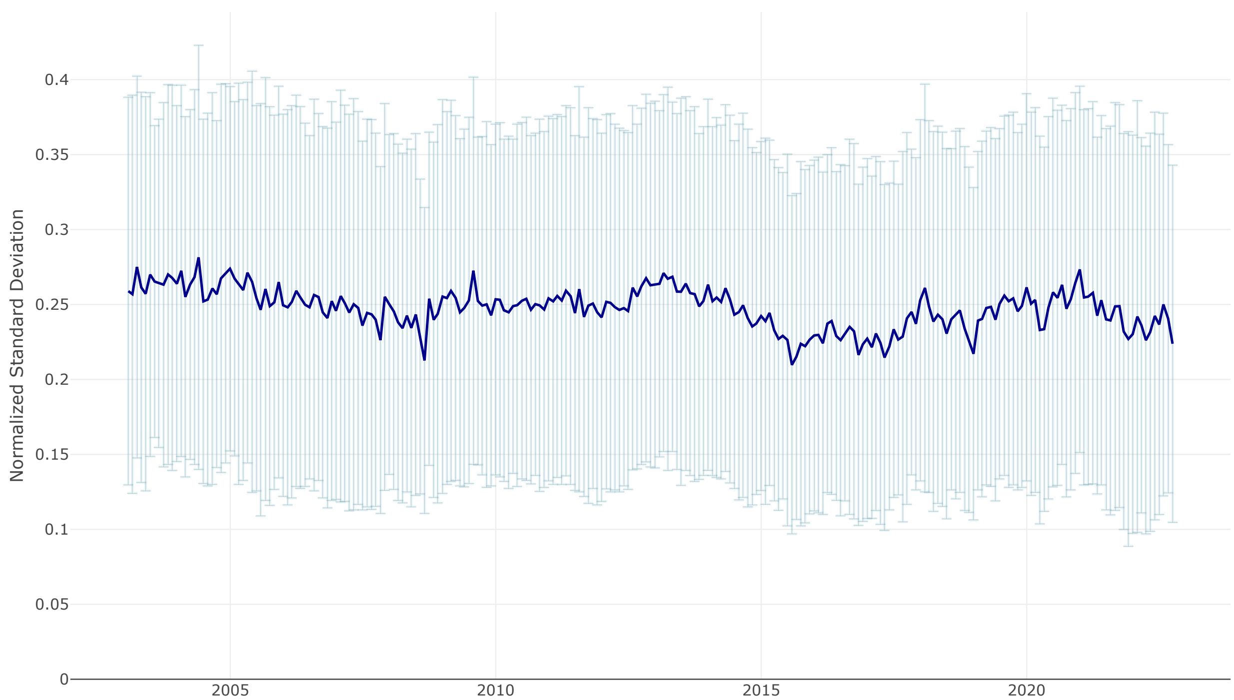
Figure C.2: Normalized Price Dispersion: Variation across Number of Bond Types



Note: This figure shows the face-value weighted normalized standard deviation of credit spread within a firm across number of bond types. Data is monthly from January 2003 to December 2023.

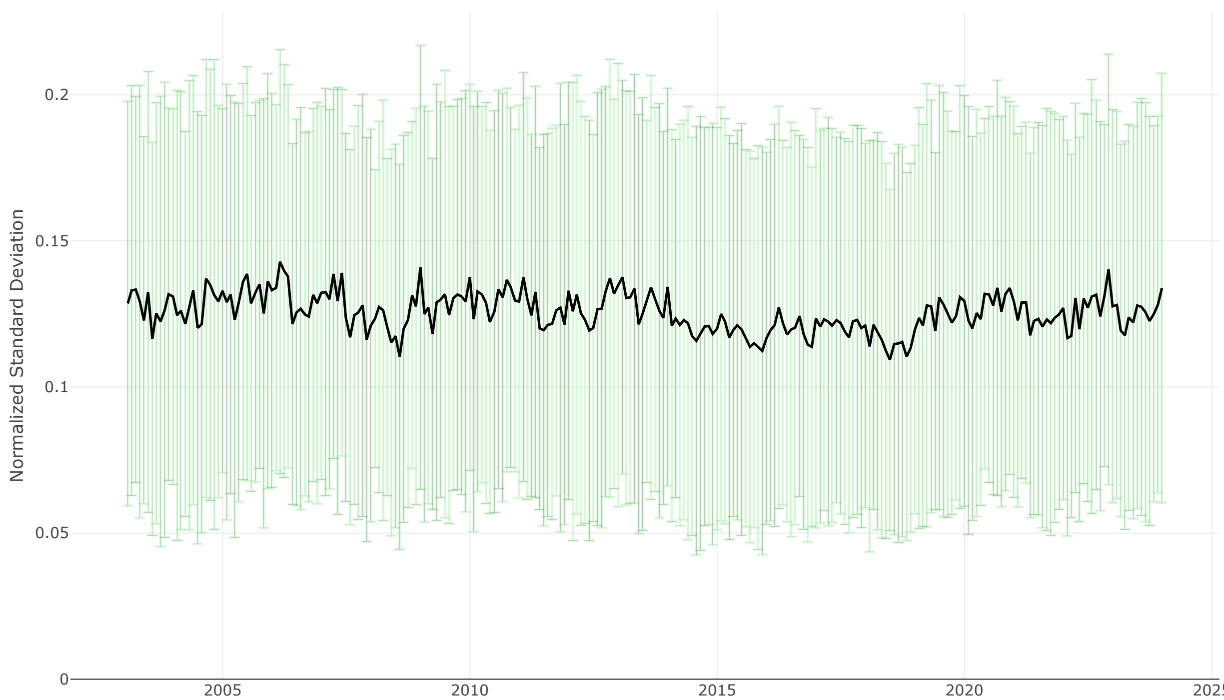
Clearly, prices should vary across bonds with differing maturities and ratings. However, these two characteristics, while important for explaining the price dispersion, do not explain all of it. Indeed, we show in Figure C.3 the remaining price dispersion when residualizing credit spreads with rating by maturity by time fixed effects. While the distribution of price dispersion across firms is lower when residualizing for these important characteristics, there is still substantial price dispersion that remains to be explained by the remaining bond characteristics. We view this as evidence that our bond type classification captures important features of corporate bonds that map to differences in prices, over and above what is explained by rating and maturity. Figure C.4 and C.5 present additional time series of normalized residual price dispersion with only long-term and A-rated bonds.

Figure C.3: Normalized Residual Price Dispersion Overtime with Interquartile Range



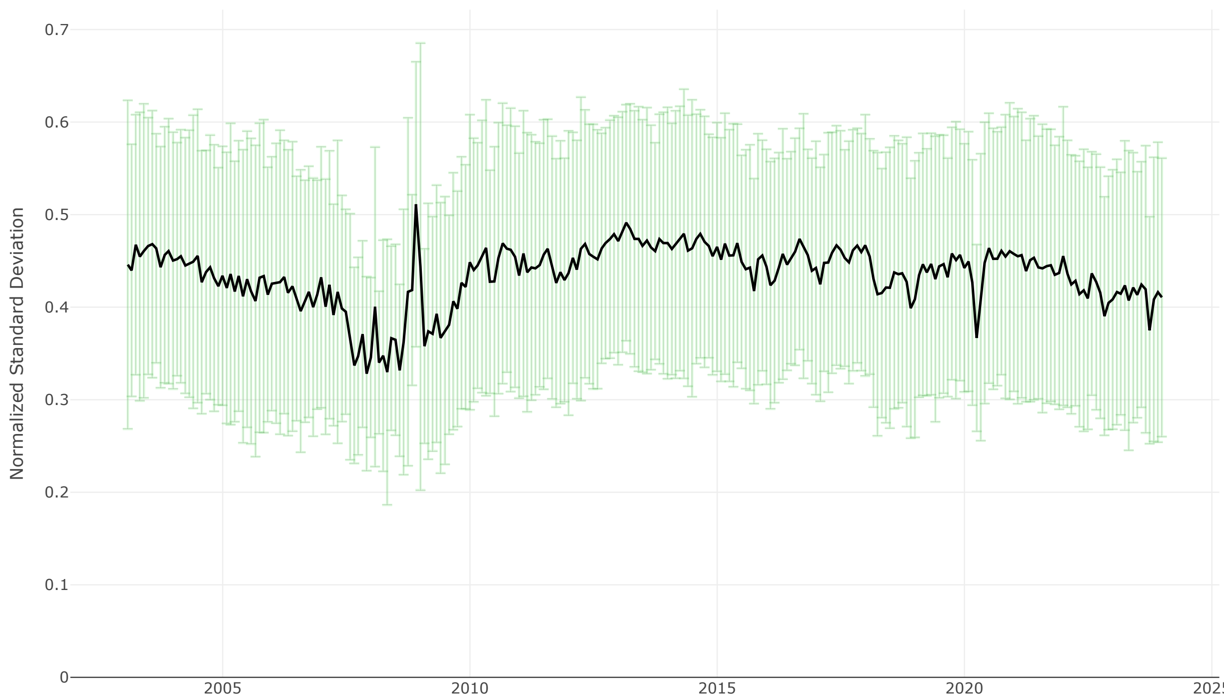
Note: This figure shows interquartile range of face-value weighted normalized standard deviations of residual credit spreads within a firm. Residual credit spread is defined as ϵ_{bft} in regression $cs_{bft} = \alpha_{rating,duration,t} + \epsilon_{bft}$. We category the duration into 5 buckets: $<$ 1 year, 1 to 3 years, 3 to 7 years, and $\geq$ 10 years. The rating buckets HY, BBB, and A refer to bonds rated BB or below, BBB, and A or above, respectively. Data is monthly from January 2003 to September 2022.

Figure C.4: Normalized Price Dispersion of Long-term Bonds



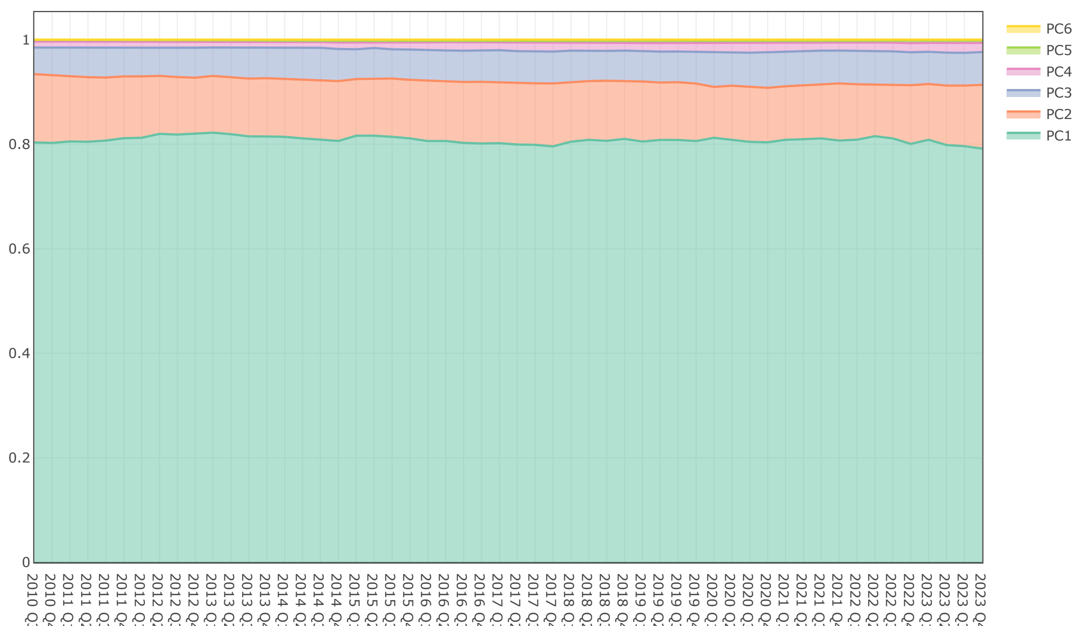
Note: This figure shows the interquartile range of face-value weighted normalized standard deviation of credit spread of long-term bonds (remaining maturity $\geq$ 10 years) within a firm. Data is monthly from January 2003 to December 2023.

Figure C.5: Normalized Price Dispersion of Bonds Rated A



Note: This figure shows the interquartile range of face-value weighted normalized standard deviation of credit spread of A-rating bonds within a firm. We define rating A as NAIC1 (ratings AAA-A). Data is monthly from January 2003 to December 2023.

Figure C.6: Variation in orthogonalized flows explained by principal components

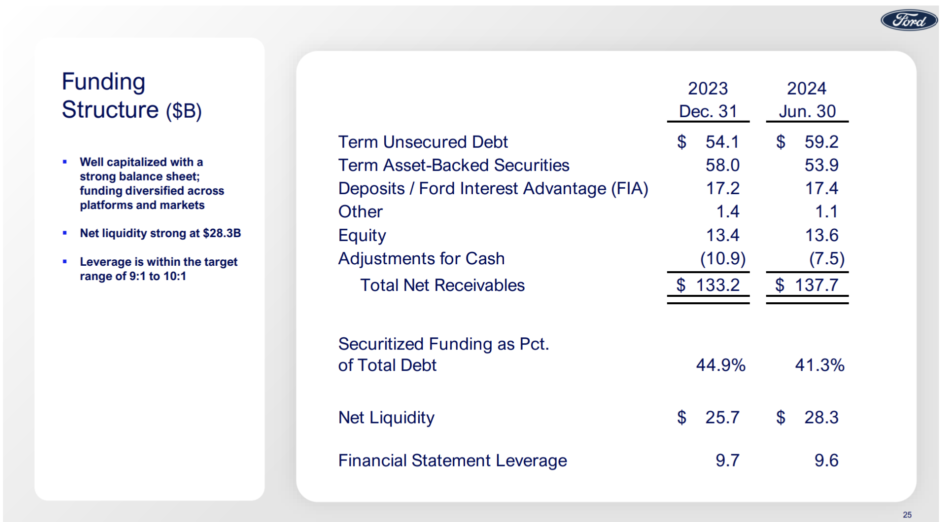


Note: This figure shows the proportion of variation explained by the principal components at each point in time, based on the cross-sectional PCA regression specified in Equation (30): $S'_{t-1} \times f^{\perp} = \alpha + \delta_{t-1}F + u$. Here, $S_{t-1} \in \mathbb{R}^{C\times N}$ denotes the time-varying matrix capturing, for each quarter, the share of outstanding bond n held by investor category c in the previous period, with each element defined as $S_{cn,t-1} = \frac{paramt_{cn,t-1}}{amtout_{n,t-1}}$. $f^{\perp} \in \mathbb{R}^{C\times T}$ is the constant time-series of weighted-average orthogonalized flows for each investor category c from 2010 Q3 to 2023 Q4, where each element is given by $f^{\perp}_{ct} = \frac{\sum_{i\in c} f^{\perp}_{it} \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$. $F \in \mathbb{R}^{1\times T}$ represents the first principal component capturing the dominant time-series factor, $\delta_{t-1} \in \mathbb{R}^{N\times 1}$ denotes the corresponding time-varying vector of loadings, interpreted as the exposure of each bond type to the common component, and $u \in \mathbb{R}^{N\times T}$ is the residual matrix. Data source: FISD, CRSP for mutual funds, NAIC for insurers.

D Extra data description

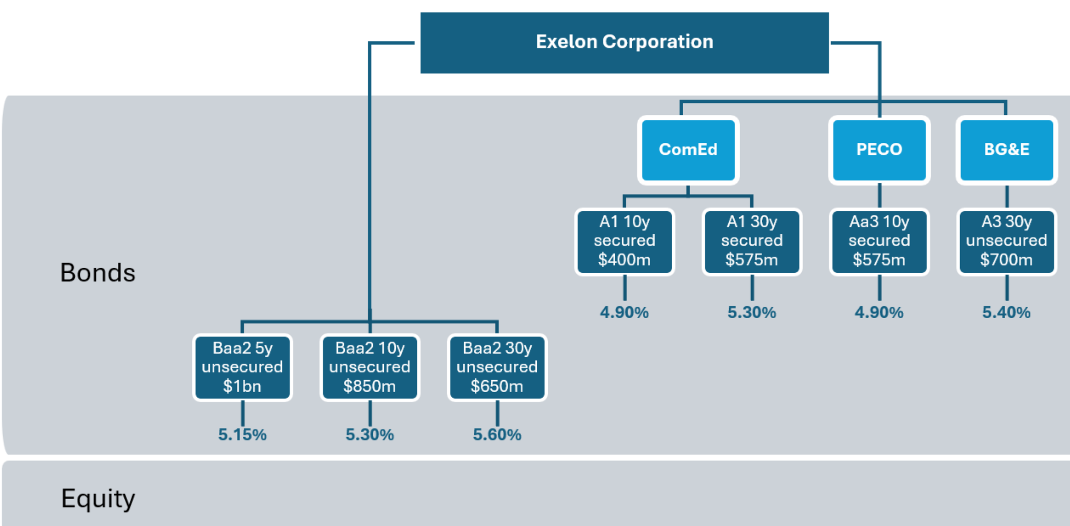
D.1 Data example

Figure D.1: Slide from Ford Investor Deck



Note: This shows a screenshot from the Ford Fixed Income Presentation at SMBC Auto Summit (Sumitomo Mitsui Banking Corporation) in September 2024. Source: Ford website.

Figure D.2: Bonds issued by Exelon Corporation in 2023



Note: This figure shows the debt issued by Exelon Corporation and its subsidiaries (i.e., Commonwealth Edison, PECO Energy, and Baltimore Gas & Electric) in 2023, conditional on bonds greater than $400 million at issuance. Coupon rates are presented below. Data source: Mergent FISD and Exelon Corporate website.

D.2 Data cleaning

We begin with the combined CRSP and NAIC corporate bond holdings dataset at the fund-bond-quarter level. To mitigate the impact of abnormal observations and extreme outliers on our baseline results, we implement four truncation steps during the data cleaning process:

1. Truncate fund-bond-quarter level $\frac{paramt_{ibt}}{amtout_{bt}}$ at [0, 1] and 99% percentile for CRSP and NAIC corporate bond holdings.

2. Truncate net flows f_{it}^{g} at 1% and 99% percentiles, separately for $g \in$ [MFs, Life insurers, P&C insurers]. Specifically,

$$f_{iq}^{MF} = \frac{AUM_{iq} - (1 + R_{iq}) \times AUM_{i,q-1}}{AUM_{i,q-1}} \tag{41}$$

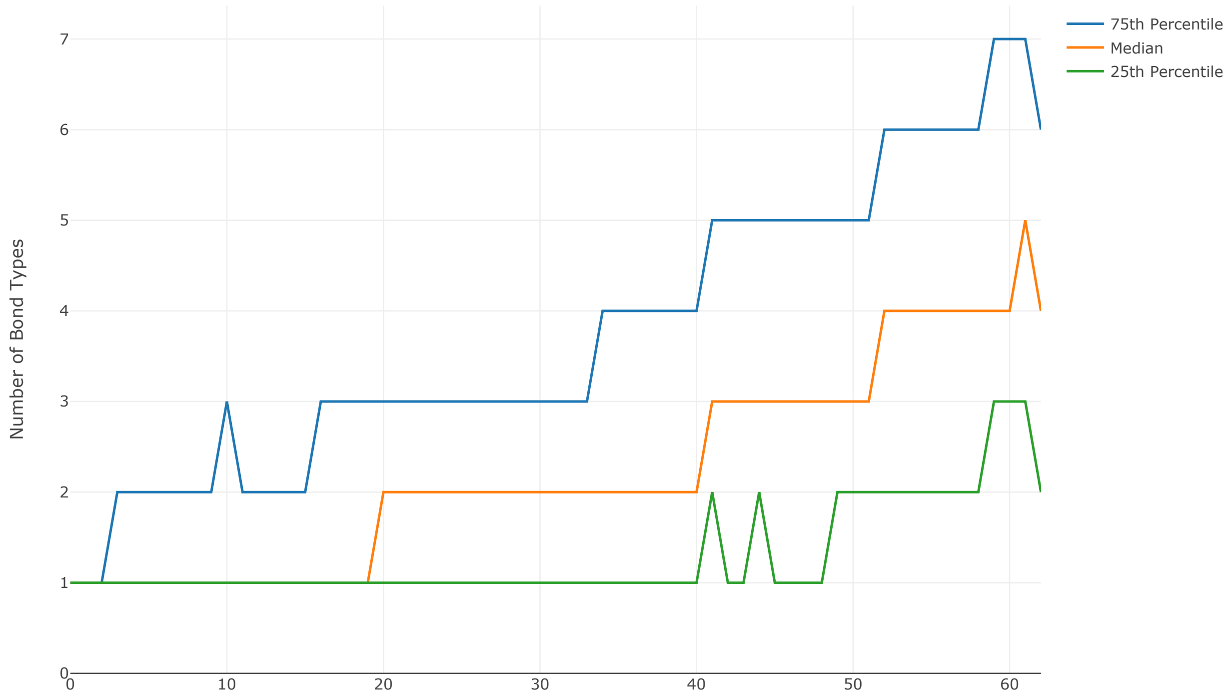
$$f_{iq}^{INS} = \frac{OperatingIncome_{iq} - OperatingIncome_{i,q-4}}{AUM_{i,q-4}} \tag{42}$$

3. Winsorize R_{it}^{g} at 1% and 99% percentiles, separately for $g \in$ [MFs, Life insurers, P&C insurers]. This variable is used when computing the fund-quarter level orthogonalized flows as constructed in Equation (24).

4. Truncate fund-bondtype-quarter level $\frac{paramt_{in,t-1}}{amtout_{n,t-1}}$ at 99% percentiles for both the aggregation of z_{nt}^{cs} (as constructed in Equation (26)) and z_{nt}^{dbr} (as constructed in Equation (31)).

D.3 Summary statistics

Figure D.3: Relationship between Firm Age and Number of Unique Bond Types



Note: This figure shows the relationship between firm age and number of unique bond types that firm issued. Firm age is defined as the number of years the firm is listed on Compustat. We report the median, the 25th, and the 75th percentiles of number of unique bond types across all firms in each age category. Data is quarterly from 2003 Q1 to 2023 Q4.

Table D.1: Investor category description

Investor Category	Description
IG/Long MFs	IG: MFs that maximum share of IG bond holdings is at least 95% Long: MFs that maximum share of holdings in bonds with time-to-maturity of over 10 years is at least 95%
IG/Short MFs	IG: MFs that maximum share of IG bond holdings is less than 95% Short: MFs that maximum share of holdings in bonds with time-to-maturity of over 10 years is less than 95%
Other/Long MFs	Other: MFs that maximum share of IG bond holdings is less than 95% Long: MFs that maximum share of holdings in bonds with time-to-maturity of over 10 years is at least 95%
Other/Short MFs	Other: MFs that maximum share of IG bond holdings is less than 95% Short: MFs that maximum share of holdings in bonds with time-to-maturity of over 10 years is less than 95%
Life Insurers	Life insurance companies
P&C Insurers	Property and casualty insurance companies

Table D.2: Average share of corporate bonds outstanding by investor category

	All Bonds	Rating			Remaining Maturity			Size		Covlite		Redemption	
		A	BBB	HY	$<$ 3 years	3 to 10 years	$\geq$ 10 years	$<$ 500 million	$\geq$ 500 million	True	False	Yes	No
All Investors	36.79	33.14	43.30	36.70	26.10	40.05	40.92	44.56	33.60	30.57	38.86	39.49	28.08
IG/Long MFs	7.35	7.56	9.11	3.29	5.42	7.51	8.61	4.79	8.14	7.73	7.23	7.36	6.84
IG/Short MFs	1.82	2.05	2.18	0.34	4.27	1.59	0.04	1.28	1.97	2.43	1.63	1.64	2.39
Other/Long MFs	5.65	0.69	2.62	22.88	2.29	8.59	3.12	6.11	5.36	3.91	6.23	6.72	2.67
Other/Short MFs	0.39	0.01	0.09	1.98	0.39	0.58	0.02	0.35	0.39	0.25	0.43	0.44	0.11
PC Insurers	3.38	4.09	3.61	1.45	3.51	4.36	1.40	3.96	3.15	3.20	3.45	3.47	2.87
Life Insurers	18.21	18.74	25.69	6.76	10.23	17.42	27.73	28.06	14.59	13.04	19.90	19.85	13.20

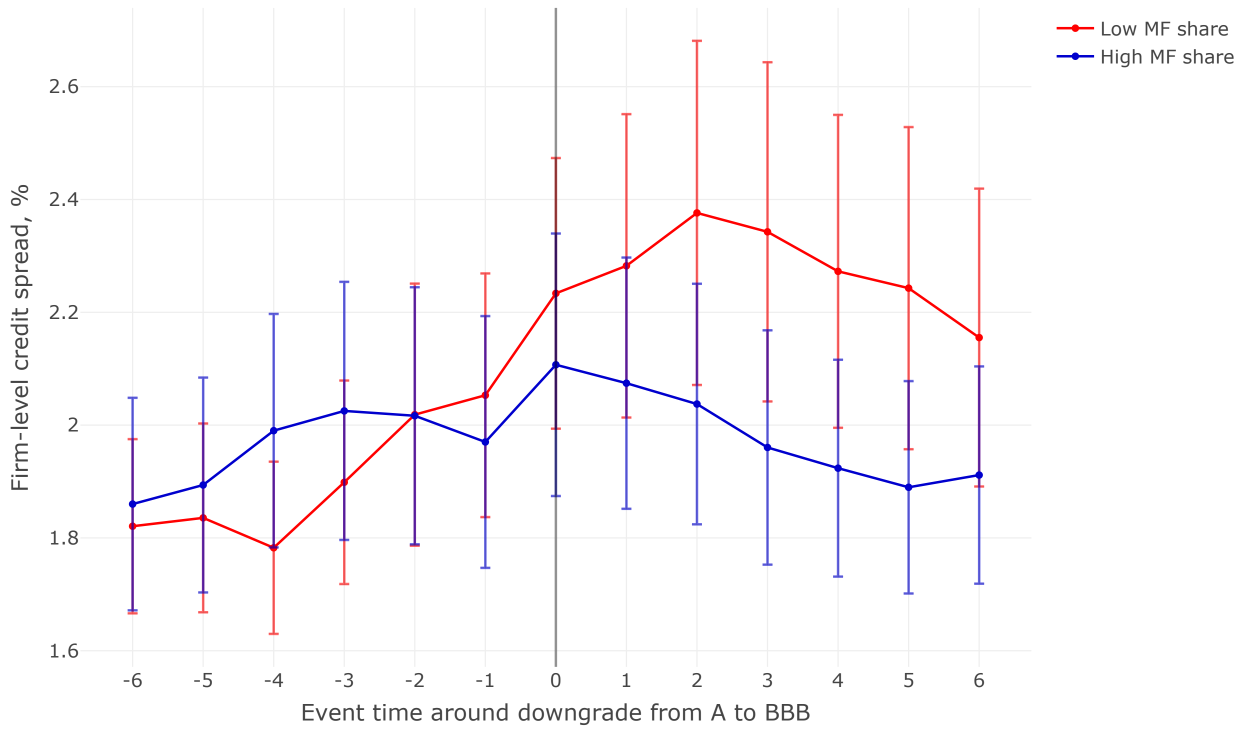
Note: This table presents the share of corporate bonds outstanding for different investor categories, segmented by the five dimensions of bond type characteristics. The share of amount outstanding is calculated by dividing the total market amount outstanding of corporate bonds with a given characteristic (from FISD) by the total par value of such bonds held by each investor category (from eMAXX). Each cell represents the average share of amount outstanding for each investor category across all periods. Data is quarterly from 2003 Q1 to 2023 Q4. Data sources: FISD, and eMAXX.

Table D.3: Share of firms with multiple issuer IDs within industry

Industry	Share of firms (%)
Utilities	39.48
Transportation and Warehousing	35.66
Finance	32.11
Real Estate	28.77
Information	25.75
Mining, Oil and Gas Extraction	24.14
Manufacturing	21.90
Retail Trade	20.17
Professional, Scientific, and Technical Services	18.97
Wholesale Trade	16.28
Full Sample	24.39

Note: This table summarizes the share of firms with multiple issuers within the top 10 industries that have the largest share of such firms. We define firms with multiple issuers as those having more than one issuers at any time point. The last row shows the the share of firms having multiple issuers across the whole sample. Data is quarterly from 2023 Q1 to 2023 Q4.

Figure D.4: Firm Weighted Average Credit Spread around Downgrade from A to BBB



Note: This figure shows the firm-level credit spread for firms with low MF share and firms with high MF share, during the period six months before and after the credit rating downgrade event from A to BBB. Firm-level credit spread is the amount outstanding-weighted credit spread for all outstanding bonds of that firm in that month, winsorized by 1% and 99%. Low MF share firms are defined as firms whose mutual fund share amount of outstanding in the previous period was below the median of the previous period; high MF share firms are the rest of firms in the sample. A downgrade event refers to when a firm's rating was above A- in the prior period, but below BBB (i.e., BBB+, BBB, or BBB-) in the present period, where firm-level rating is the highest credit rating across all outstanding bonds of that firm in that period.

E Model proofs

E.1 The agent's problem

There are I investors who can invest in N risky assets issued by the firm or in a risk-free bond in elastic supply. Each asset is priced at par (each price = 1) and the risk-free bond interest rate is equal to zero. Each risky asset n has gross return $R(n)$, and excess return $\boldsymbol{r} = \boldsymbol{R} - \mathbf{1}$.

Assume there are K_r factors, $\boldsymbol{f} \in \mathbb{R}^{K_r}$, that drive the covariance structure of excess returns, such that for each asset n

$$r(n) = \mu(n) + \boldsymbol{\beta}(n)^\top \boldsymbol{f} + \epsilon_r(n) \tag{43}$$

where $\mathbb{E}[f_k] = \mathbf{0}$, $\mathbb{E}[\epsilon_r] = \mathbf{0}$, $Cov(\boldsymbol{R}) = \Sigma_r = \boldsymbol{\beta}^\top \Sigma_f \boldsymbol{\beta} + \Sigma_{\epsilon_r}$, $Cov(\boldsymbol{f}) = \Sigma_f$ and $Cov(\boldsymbol{\epsilon}_r) = \Sigma_{\epsilon_r} = \sigma^2_{\epsilon_r}(n)\mathbb{I}$.

Investors are born with investable wealth W_{i0} and are subject to background risk with loading $\boldsymbol{\theta}_i$ on the factors $\boldsymbol{f}$. Let ω_{if} and $\boldsymbol{\omega}_i$ be the portfolio weights on the risk-free assets and the risky assets, respectively. The second-period wealth, W_i', is

$$W_i' = W_{i0}\big[\omega_i^f + \omega^\top \boldsymbol{R} - \boldsymbol{\theta}_i^\top \boldsymbol{f}\big].$$

or

$$\frac{W_i'}{W_{i0}} = 1 + \boldsymbol{\omega}_i^\top \boldsymbol{r} - \boldsymbol{\theta}_i^\top \boldsymbol{f}.$$

Investors choose portfolio weights to maximize

$$\max_{\omega_i^f \in \mathbb{R}, \boldsymbol{\omega}_i \in \mathbb{R}^N} \quad \mathbb{E}[W_i'] - \frac{\gamma_i}{2}\mathrm{Var}(W_i'), \tag{44}$$

$$\text{s.t.} \quad \mathbf{1}^\top \boldsymbol{\omega}_i + \omega_i^f = 1 \tag{45}$$

$$\omega_{fi} \geq 0 \text{ and } \boldsymbol{\omega}_i \geq \mathbf{0}. \tag{46}$$

Define the factor-asset covariance

$$\boldsymbol{h} = \mathrm{Cov}(\boldsymbol{R}, \boldsymbol{f}) \ \in \ \mathbb{R}^{N \times K_r}.$$

Using the above,

$$\mathrm{Var}(W_i') = W_{i0}^2 \Big[\underbrace{\boldsymbol{\omega}_i^\top \Sigma_r \boldsymbol{\omega}_i}_{(1\times N)(N\times N)(N\times 1)} - 2 \underbrace{\boldsymbol{\omega}_i^\top \boldsymbol{h} \boldsymbol{\theta}_i}_{\substack{(1\times N)(N\times K_r)\\(K_r\times 1)}} + \underbrace{\boldsymbol{\theta}_i^\top \Sigma_f \boldsymbol{\theta}_i}_{(1\times K_r)(K_r\times K_r)(K_r\times 1)} \Big].$$

The expectation and variance of wealth is thus:

$$\begin{aligned}
\mathbb{E}[W_i'] &= W_{i0}\Big[1 + \mathbb{E}[\boldsymbol{r}]^\top \boldsymbol{\omega}_i\Big], \\
\mathrm{Var}(W_i') &= W_{i0}^2\Big[\boldsymbol{\omega}_i^\top \Sigma_r \boldsymbol{\omega}_i - 2\boldsymbol{\omega}_i^\top \boldsymbol{h}\boldsymbol{\theta}_i + \boldsymbol{\theta}_i^\top \Sigma_f \boldsymbol{\theta}_i\Big].
\end{aligned}$$

Introduce multipliers $\boldsymbol{\lambda}_i \geq \mathbf{0}$ for $\boldsymbol{\omega}_i \geq \mathbf{0}$, and $\lambda_{if} \geq 0$ for $\mathbf{1}^\top \boldsymbol{\omega}_i \leq 1$. We can write out the Lagrangian as:

$$\begin{aligned}
\mathcal{L}(\boldsymbol{\omega}_i, \boldsymbol{\lambda}_i, \lambda_{if}) = W_{i0}\big[1 + \boldsymbol{\mu}^\top \boldsymbol{\omega}_i\big] - \frac{\gamma_i W_{i0}^2}{2}\Big[\boldsymbol{\omega}_i^\top \Sigma_r \boldsymbol{\omega}_i - 2\boldsymbol{\omega}_i^\top \boldsymbol{h}\boldsymbol{\theta}_i + \boldsymbol{\theta}_i^\top \Sigma_f \boldsymbol{\theta}_i\Big] \\
+ \ \boldsymbol{\lambda}_i^\top \boldsymbol{\omega}_i \ + \ \lambda_{if}\big[1 - \mathbf{1}^\top \boldsymbol{\omega}_i\big].
\end{aligned}$$

where we substitute $\omega_{fi} = 1 - \mathbf{1}^\top \boldsymbol{\omega}_i$. The no-borrowing constraint $\omega_{fi} \geq 0$ becomes $\mathbf{1}^\top \boldsymbol{\omega}_i \leq 1$.

From the agent's first order condition, we have

$$\frac{\partial \mathcal{L}}{\partial \boldsymbol{\omega}_i} = W_{i0}\boldsymbol{\mu} - \gamma_i W_{i0}^2\big(\Sigma_r \boldsymbol{\omega}_i - \boldsymbol{h}\boldsymbol{\theta}_i\big) + \boldsymbol{\lambda}_i - \lambda_{if}\mathbf{1} = 0$$

and the complementary slack conditions

$$\lambda_{i,k}\omega_{i,k} = 0, \quad \lambda_{i,k} \geq 0, \ \omega_{i,k} \geq 0, \qquad \lambda_{if}\big[1 - \mathbf{1}^\top \boldsymbol{\omega}_i\big] = 0, \quad \lambda_{if} \geq 0, \ 1 - \mathbf{1}^\top \boldsymbol{\omega}_i \geq 0.$$

Hence, the optimal portfolio choice is

$$\boxed{\boldsymbol{\omega}_i^* = \frac{1}{\gamma_i W_{i0}}\,\Sigma_r^{-1}\Big[\boldsymbol{\mu} + \gamma_i W_{i0}\,\boldsymbol{h}\,\boldsymbol{\theta}_i + \frac{1}{W_{i0}}\big(\boldsymbol{\lambda}_i + \lambda_{if}\mathbf{1}\big)\Big]} \tag{47}$$

It is useful to notice that ω_i^* is linear on $\boldsymbol{\mu}$, $\boldsymbol{h}$ and $\boldsymbol{\beta}$. We use the Woodbury matrix identity to get:

$$\Sigma_r^{-1} = \Sigma_{\epsilon_r}^{-1} - \Sigma_{\epsilon_r}^{-1}\,\beta^\top\big(\Sigma_f^{-1} + \beta\,\Sigma_{\epsilon_r}^{-1}\,\beta^\top\big)^{-1}\beta\,\Sigma_{\epsilon_r}^{-1} \tag{48}$$

Plugging into Equation 47, we get:

$$\boxed{\boldsymbol{\omega}_i^* = \frac{1}{\gamma_i W_{i0}}\Sigma_{\epsilon_r}^{-1}\Big[\boldsymbol{\mu} + \gamma_i W_{i0}\,\boldsymbol{h}\,\boldsymbol{\theta}_i + \tfrac{1}{W_{i0}}\big(\boldsymbol{\lambda}_i - \lambda_{if}\,\mathbf{1}\big) - \boldsymbol{\beta}^\top\boldsymbol{\kappa}_i\Big]} \tag{49}$$

where $\kappa_i = D_r\,\beta\,\Sigma_{\epsilon_r}^{-1}\tilde{\boldsymbol{\mu}}_i$, $D_r = \left(\Sigma_f^{-1} + \beta\,\Sigma_{\epsilon_r}^{-1}\,\beta^\top\right)^{-1}$ and $\tilde{\boldsymbol{\mu}}_i = \boldsymbol{\mu} + \gamma_i W_{i0}\,\boldsymbol{h}\,\boldsymbol{\theta}_i + \frac{1}{W_{i0}}\big(\boldsymbol{\lambda}_i - \lambda_{if}\,\mathbf{1}\big)$.

We can then write optimal portfolio choice as:

$$\boxed{\boldsymbol{\omega}_i^* = \frac{1}{\gamma_i W_{i0}}\Sigma_{\epsilon_r}^{-1}\Big[\tilde{\boldsymbol{\mu}}_i - \boldsymbol{\beta}^\top\boldsymbol{\kappa}_i\Big]} \tag{50}$$

E.2 The Firm's Problem

A firm seeks to finance a profitable investment with cost c that generates certain dividends D. Given the absence of uncertainty in D, this investment could be fully financed with risk-free debt.

However, the firm has an alternative strategy: it can partition the investment into subprojects and issue bonds backed by each component. Under this approach, the firm issues N distinct risky bonds at par value, raising total proceeds of $\boldsymbol{q}^\top\mathbf{1}$, where $\boldsymbol{q} \in \mathbb{R}^N$ represents the vector of issuance quantities across all bonds. Each bond n has specific risk characteristics. Bond n repays $R(n)$ with probability $\pi(n)$, or defaults with complete loss (repaying zero) with probability $1 - \pi(n)$.

The firm also recognizes a funding risk associated with each bond type n. This funding risk comprises two components: investor demand shocks and bond-specific issuance costs. The investor demand shock maps to either shocks on preferences or wealth. Even though our model is static, it represents in reduced form the impact of the refinancing cost on the firm.

Let $\iota(n)$ denote the funding risk of bond n. We assume there are K_ι factors, $\boldsymbol{g} \in \mathbb{R}^{K_\iota}$, driving investor demand and a $\epsilon_\iota(n)$ a idiosyncratic cost. The funding risk can be formally expressed as

$$\iota(n) = \bar{\iota}(n) + \boldsymbol{\delta}(g)^\top \boldsymbol{g} + \epsilon_\iota(n) \tag{51}$$

where $\mathbb{E}[\boldsymbol{g}] = \mathbf{0}$, $\mathbb{E}[\epsilon_\iota] = 0$, $Cov(\boldsymbol{\iota}) = \Sigma_\iota$. $Cov(\boldsymbol{g}) = \Sigma_g$, and $Cov(\boldsymbol{\epsilon}_\iota) = \Sigma_{\epsilon_\iota} = diag(\boldsymbol{\sigma}^2_{\epsilon_\iota})$. Notice this means $\Sigma_\iota = \boldsymbol{\delta}^\top \Sigma_g \boldsymbol{\delta} + \Sigma_{\epsilon_\iota}$.

The firm's objective is to determine the optimal financing strategy by maximizing financing efficiency while managing funding risk. Let $\gamma_f > 0$ be the firm's funding risk with aversion. It chooses its debt structure to maximize

$$\max_{\boldsymbol{q} \in \mathbb{R}^N} \quad \mathbb{E}[D + \boldsymbol{q}^\top(\mathbf{1} - \boldsymbol{R})] - \frac{\gamma_f}{2} \boldsymbol{q}^\top \Sigma_\iota \boldsymbol{q} \tag{52}$$

$$\text{s.t.} \quad \boldsymbol{q}^\top \mathbf{1} \geq c, \boldsymbol{q} \geq \mathbf{0} \tag{53}$$

$$\boldsymbol{q}^\top(\mathbf{1} - \boldsymbol{R}(s)) + (D - c) \geq 0 \; \forall \text{ all states } s, \tag{54}$$

We assume that D is large enough such that the financing constraint is not binding and that the demand for bonds is such that the short-selling constraint is not binding. In that case, the optimal issuance decision is

$$\boxed{\boldsymbol{q}^* = \frac{1}{\gamma_f} \Sigma_\iota^{-1}(\mathbf{1} - \mathbb{E}[\boldsymbol{R}]) = -\frac{1}{\gamma_f} \Sigma_\iota^{-1} \boldsymbol{\mu}} \tag{55}$$

where $\boldsymbol{\mu} = \mathbb{E}[\boldsymbol{R}] - \mathbf{1}$ is an expected (excess) return with dimensions and Σ_ι represents the funding risk associated with the portfolio of bonds the firm has outstanding.

It is useful the notice that $\boldsymbol{q}^*$ is linear in $\boldsymbol{\mu}$ and $\boldsymbol{\delta}$, the funding risk's loading on the common factor. To see this, we can use the Woodburry matrix identity,

$$\Sigma_{\iota}^{-1} = \Sigma_{\epsilon_\iota}^{-1} - \Sigma_{\epsilon_\iota}^{-1}\,\delta^\top \left(\Sigma_g^{-1} + \delta\,\Sigma_{\epsilon_\iota}^{-1}\,\delta^\top\right)^{-1} \delta\,\Sigma_{\epsilon_\iota}^{-1} \tag{56}$$

We plug this into the firm's optimal issuance decision and get:

$$\boldsymbol{q}_S^* = -\frac{1}{\gamma_f}\,\Sigma_{\epsilon_\iota}^{-1}\Big[\boldsymbol{\mu} - \boldsymbol{\delta}^\top \boldsymbol{\kappa}_f\Big]. \tag{57}$$

where $\kappa_f = D_\iota \boldsymbol{\delta}\,\Sigma_{\epsilon_\iota}^{-1}\boldsymbol{\mu}$, a $K_\iota \times 1$ vector that is importantly constant across assets and $D_\iota = \left(\Sigma_g^{-1} + \delta\,\Sigma_{\epsilon_\iota}^{-1}\,\delta^\top\right)^{-1}$ is a a $K_\iota \times K_\iota$ matrix. The one-asset version can be written:

$$q_S^*(n) = \frac{1}{\gamma_f \sigma_{\epsilon_\iota}^2(n)}\Big[\mu(n) - \boldsymbol{\delta}^\top(n)\boldsymbol{\kappa}_f\Big] \tag{58}$$

E.3 Equilibrium in the Bond Market

Aggregate Demand

For simplicity assume $W_{i0}\gamma_i = \gamma_d, \forall i$. The total bonds demand is

$$\begin{aligned}
\boldsymbol{q}^D &= \sum_i W_{i0}\omega_i^* && (59)\\
&= \frac{1}{\gamma_d}\sum_i W_{i0}\Sigma_{\epsilon_r}^{-1}\left[\boldsymbol{\mu} + \gamma_d \boldsymbol{h}\boldsymbol{\theta}_i + \frac{1}{W_{i0}}\tilde{\boldsymbol{\lambda}}_i - \boldsymbol{\beta}^\top \boldsymbol{\kappa}_i\right] && (60)\\
&= \frac{1}{\gamma_d}\Sigma_{\epsilon_r}^{-1}\left[\boldsymbol{\mu}W_0 + \gamma_d \boldsymbol{h}\sum_i W_{i0}\theta_i + \sum_i \tilde{\boldsymbol{\lambda}}_i - \boldsymbol{\beta}^\top \sum_i W_{i0}\boldsymbol{\kappa}_i\right] && (61)\\
&= \frac{W_0}{\gamma_d}\Sigma_{\epsilon_r}^{-1}\left[\boldsymbol{\mu} + \gamma_d \boldsymbol{h}\bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}}\right] && (62)
\end{aligned}$$

where $W_0 = \sum_i W_{oi}$ is the total investable wealth in the economy, $\tilde{w}_i = \frac{W_{0i}}{W_0}$ is agent i's share of aggregate wealth. We further define $\bar{\boldsymbol{\theta}} = \sum_i \tilde{w}_i \boldsymbol{\theta}_i$ as the $K_r \times 1$ wealth-weighted average background-risk loading on non-tradable factors, $\bar{\boldsymbol{\lambda}} = \frac{1}{W_0}\sum_i \tilde{\lambda}_i$ is the $N \times 1$ economy-wide tightness trading constraints per unit of wealth, and $\bar{\boldsymbol{\kappa}} = \sum_i \tilde{w}_i \boldsymbol{\kappa}_i$ is the $K_r \times 1$ wealth-weighted average hedge-portfolio that strips out the systematic component of expected returns.

Recall $\boldsymbol{h}$ is $K_r \times N$, $\boldsymbol{\mu}$ is $N \times 1$, and $\Sigma_{\epsilon_r}^{-1}$ is $N \times N$. The one-asset version of aggregate demand is thus:

$$q^D(n) = \frac{W_0}{\gamma_d \sigma_{\epsilon_r}^2(n)} \Big[\mu(n) + \gamma_d \boldsymbol{h}(n)\bar{\boldsymbol{\theta}} + \lambda(\bar{n}) - \boldsymbol{\beta}^\top(n)\bar{\boldsymbol{\kappa}}\Big] \tag{63}$$

Market Clearing

Equate supply and demand:

$$\boldsymbol{q}^S = \boldsymbol{q}^D \tag{64}$$

$$\Longrightarrow -\frac{1}{\gamma_f}\Sigma_{\epsilon_\iota}^{-1}\Big[\boldsymbol{\mu} - \boldsymbol{\delta}^\top \boldsymbol{\kappa}_f\Big] = \frac{W_0}{\gamma_d}\Sigma_{\epsilon_r}^{-1}\Big[\boldsymbol{\mu} + \gamma_d \boldsymbol{h}\bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}}\Big] \tag{65}$$

$$\Longrightarrow \boldsymbol{\mu} = \left(\frac{1}{\gamma_f}\Sigma_{\epsilon_\iota}^{-1} + \frac{W_0}{\gamma_d}\Sigma_{\epsilon_r}\right)^{-1}\left[\frac{1}{\gamma_f}\Sigma_{\epsilon_r}^{-1}\boldsymbol{\delta}^\top \boldsymbol{\kappa}_f - \frac{W_0}{\gamma_d}\Sigma_{\epsilon_r}^{-1}\Big(\gamma_d \boldsymbol{h}\bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}}\Big)\right] \tag{66}$$

Also we can write the linear equation for a given asset n:

$$\boldsymbol{q}^S(n) = \boldsymbol{q}^D(n) \tag{67}$$

$$\Longrightarrow \frac{W_0}{\gamma_d \sigma_r^2(n)}\Big[\mu(n) + \gamma_d \boldsymbol{h}(n)^\top \bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}}(n) - \boldsymbol{\beta}(n)^\top \bar{\boldsymbol{\kappa}}\Big] = -\frac{1}{\gamma_f \sigma_\iota^2(n)}\Big[\mu(n) - \boldsymbol{\delta}(n)^\top \boldsymbol{\kappa}_f\Big] \tag{68}$$

$$\Longrightarrow \mu(n) = \left(\frac{W_0}{\gamma_d \sigma_r^2(n)} + \frac{1}{\gamma_f \sigma_\iota^2(n)}\right)^{-1}\left[\frac{W_0}{\gamma_d \sigma_r^2(n)}(-\gamma_d \bar{\boldsymbol{\theta}}^\top \boldsymbol{h}(n) - \bar{\boldsymbol{\lambda}}(n) + \bar{\boldsymbol{\kappa}}^\top \boldsymbol{\beta}(n)) + \frac{1}{\gamma_f \sigma_\iota^2(n)}\boldsymbol{\delta}(n)^\top \boldsymbol{\kappa}_f\right] \tag{69}$$

$$\Longrightarrow \mu(n) = B_\theta(n)\cdot \bar{\boldsymbol{\theta}}^\top \boldsymbol{h}(n) + B_\lambda(n)\cdot \bar{\boldsymbol{\lambda}}(n) + B_\beta(n)\cdot \boldsymbol{\beta}(n) + B_\delta(n)\cdot \boldsymbol{\delta}(n) \tag{70}$$

where

$$A(n) = \left(\frac{W_0}{\gamma_d \sigma_r^2(n)} + \frac{1}{\gamma_f \sigma_\iota^2(n)} \right)^{-1} \tag{71}$$

$$B_\theta(n) = -A(n) \cdot \frac{W_0}{\sigma_r^2(n)} \tag{72}$$

$$B_\lambda(n) = -A(n) \cdot \frac{W_0}{\gamma_d \sigma_r^2(n)} \tag{73}$$

$$B_\beta(n) = A(n) \cdot \frac{W_0}{\gamma_d \sigma_r^2(n)} \bar{\boldsymbol{\kappa}}^\top \tag{74}$$

$$B_\delta(n) = A(n) \cdot \frac{1}{\gamma_f \sigma_\iota^2(n)} \kappa_f \tag{75}$$

F Additional results on the issuance analyses

F.1 Simple OLS

Table F.1: OLS analysis: How Firms Respond to Relative Credit Spreads

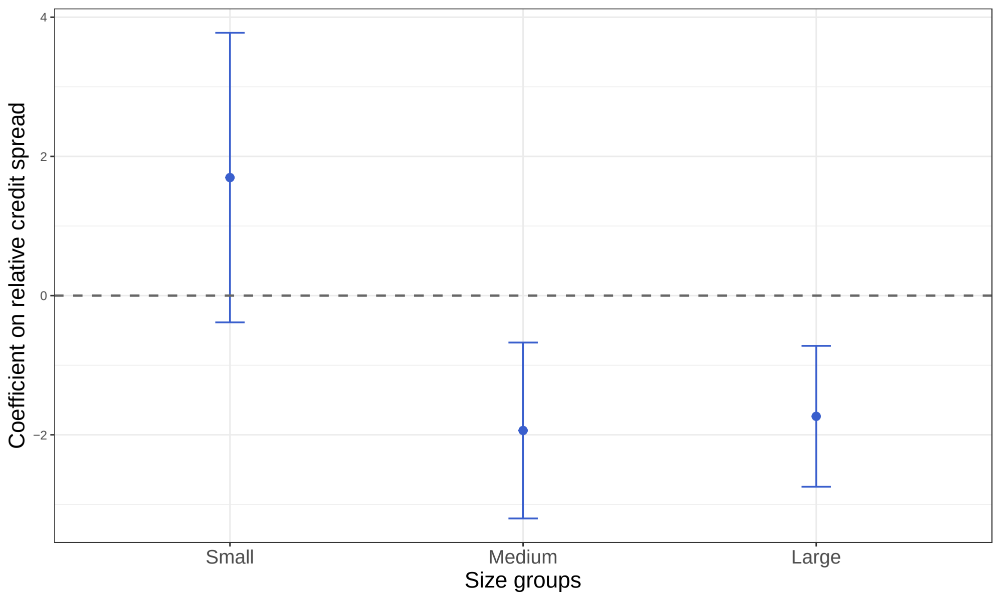
	$issuance_{fnt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	-0.006	-0.011			-0.006	-0.011
	(0.008)	(0.009)			(0.008)	(0.009)
$dbr_{n,t-1}$: Demand-based risk			-0.115^{*}	-0.107^{*}	-0.115^{*}	-0.107^{*}
			(0.059)	(0.059)	(0.059)	(0.059)
$Tobin's\ Q_{f,t-1}$	0.071^{*}		0.072^{*}		0.072^{*}	
	(0.043)		(0.043)		(0.043)	
$Leverage_{f,t-1}$	-0.190^{***}		-0.188^{***}		-0.188^{***}	
	(0.044)		(0.044)		(0.044)	
$Debt\ coming\ due_{f,t-1}$	1.569^{***}		1.570^{***}		1.570^{***}	
	(0.249)		(0.249)		(0.249)	
$Average\ CDS_{f,t-1}$	-0.667^{**}		-0.640^{**}		-0.640^{**}	
	(0.263)		(0.262)		(0.262)	
$Log\ assets_{f,t-1}$	-0.069^{***}		-0.069^{***}		-0.069^{***}	
	(0.011)		(0.011)		(0.011)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
Observations	133,094	133,094	133,094	133,094	133,094	133,094
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the OLS results of how relative bond type credit spreads in the previous period would affect the firm's issuance of bond type n in period t. The regression panel is at the firm-bond type-quarter level, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. The sample spans 2010 Q3 to 2023 Q4 and includes non-financial firms with at least $1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The outcome variable is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's quarterly total asset in the prior period. The independent variable and instrument variable are constructed from Equation (27). The firm-level characteristics in the previous period include Tobin's Q, leverage (financial-debt-to-assets ratio), average CDS spread, debt coming due, and funding risk. We winsorize $cs^r_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level. Data source: FISD, Compustat, WRDS Bond Returns, and Markit CDS.

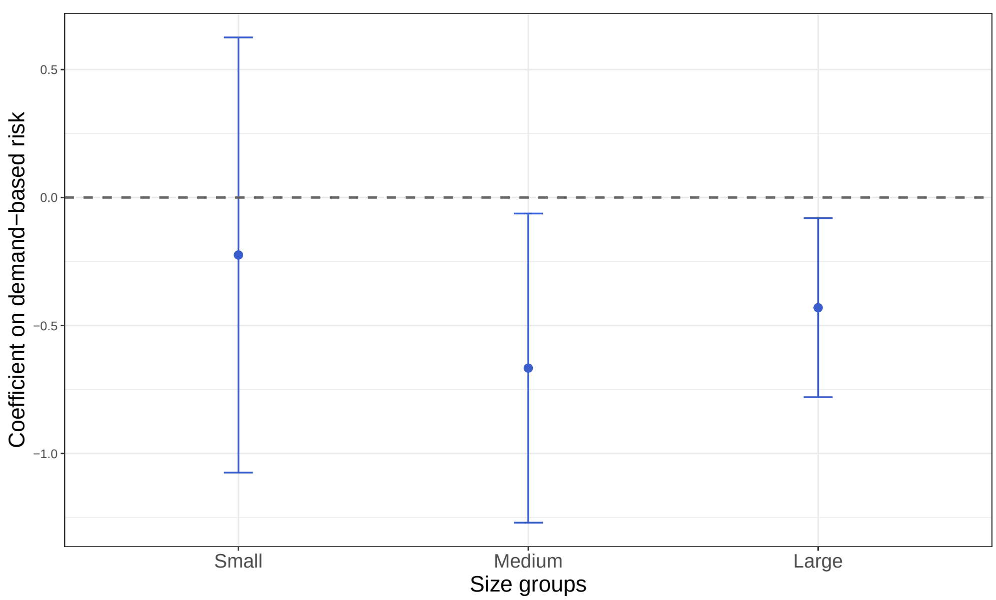
F.2 IV heterogeneous effects

Figure F.1: IV heterogeneous effects: subsample by firm size

a. Second-stage estimates on relative credit spreads



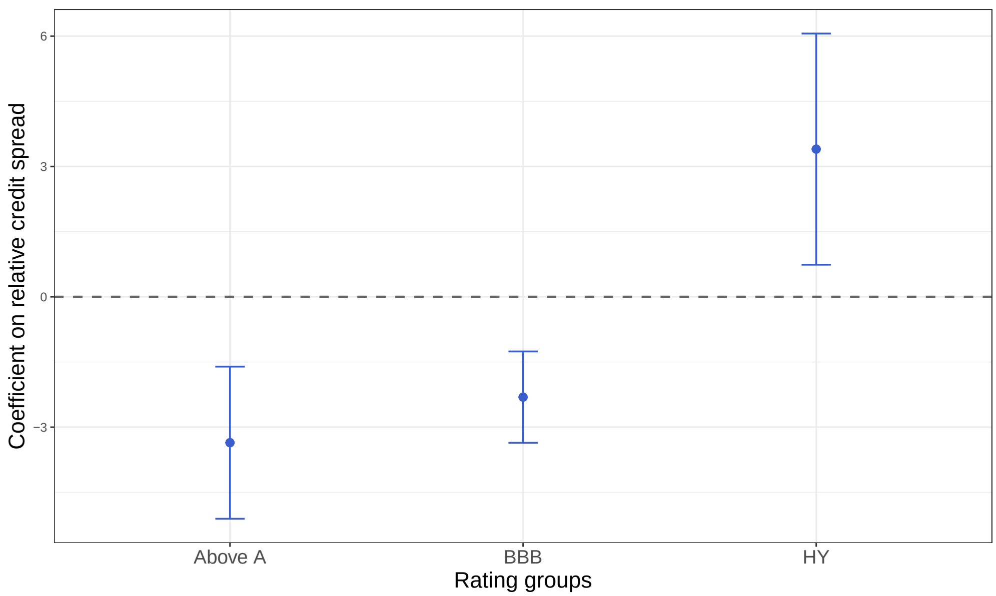
b. Second-stage estimates on demand-based risk



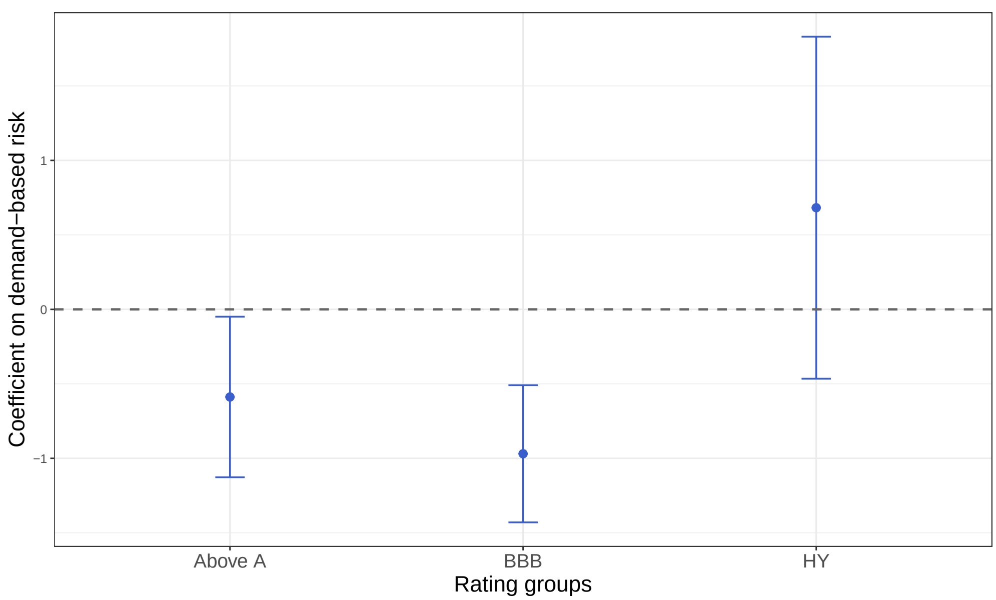
Note: This figure shows the IV heterogeneous effects, subsampling by firms' size in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). We control for firm characteristics including Tobin's Q, leverage, average CDS, debt coming due, and log assets in the previous period. Firm fixed effect and month fixed effect are included. Data is quarterly from 2010 Q3 to 2023 Q4. We winsorize $cs^{r}_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level.

Figure F.2: IV heterogeneous effects: subsample by firm credit rating

a. Second-stage estimates on relative credit spreads



b. Second-stage estimates on demand-based risk



Note: This figure shows the IV heterogeneous effects, subsampling by firms' maximum credit rating in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). We control for firm characteristics including Tobin's Q, leverage, average CDS, debt coming due, and log assets in the previous period. Firm fixed effect and month fixed effect are included. Data is quarterly from 2010 Q3 to 2023 Q4. We winsorize $cs^r_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level.

F.3 Issuing a new bond type

Table F.2: How relative credit spread and demand-based risk affect firms new issue

	$\mathbb{1}[new\_bondtype]_{fnt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	-0.305^{***}	-0.306^{***}			-0.330^{***}	-0.367^{***}
	(0.083)	(0.084)			(0.093)	(0.107)
$dbr_{n,t-1}$: Demand-based risk			0.029	0.023	-0.040	-0.076^{*}
			(0.028)	(0.026)	(0.036)	(0.042)
$Tobin's\ Q_{f,t-1}$	0.001		0.001		0.001	
	(0.013)		(0.011)		(0.013)	
$Leverage_{f,t-1}$	-0.062^{***}		-0.061^{***}		-0.062^{***}	
	(0.012)		(0.012)		(0.012)	
$Debt\ coming\ due_{f,t-1}$	0.401^{***}		0.411^{***}		0.400^{***}	
	(0.067)		(0.063)		(0.067)	
$Average\ CDS_{f,t-1}$	-0.106		-0.107^{*}		-0.099	
	(0.082)		(0.063)		(0.085)	
$Log\ assets_{f,t-1}$	-0.014^{***}		-0.013^{***}		-0.013^{***}	
	(0.003)		(0.003)		(0.003)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	20.35	94.58	290.19	2510.13	99.07	59.92
Observations	133,094	133,094	133,094	133,094	133,094	133,094
Note:				*p<0.1; **p<0.05; ***p<0.01		

Note: This table shows how variation in demand-based risk would impact firm's decision of issuing a new bond type, conditional on prices. The regression panel is at the firm-bond type-quarter level, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. The sample spans 2010 Q3 to 2023 Q4 and includes non-financial firms with at least $1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The independent variable $\mathbb{1}[new\_bondtype]_{fnt} = 1$ if the firm f has no outstanding for the bond type n in the past 12 months. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize $cs^r_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

F.4 Robustness

Table F.3: Baseline IV using only flows from retail MFs

Panel A: First stage test for flow-based instruments						
	$cs^r_{fk,t-1}$		$dbr_{k,t-1}$		$cs^r_{fk,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{n,t-1}$: Exogenous net flows	-0.372^{***}	-0.326^{***}			-0.379^{***}	-0.320^{***}
	(0.009)	(0.011)			(0.010)	(0.011)
$z^{dbr}_{n,t-1}$			0.475^{***}	0.559^{***}	0.045^{***}	-0.034^{**}
			(0.004)	(0.004)	(0.015)	(0.016)
$Tobin's\ Q_{f,t-1}$	-0.004		0.012^{***}		-0.004	
	(0.011)		(0.003)		(0.011)	
$Leverage_{f,t-1}$	-0.010		0.014^{***}		-0.011	
	(0.008)		(0.002)		(0.008)	
$Debt\ coming\ due_{f,t-1}$	-0.026		0.022^{*}		-0.025	
	(0.046)		(0.012)		(0.046)	
$Average\ CDS_{f,t-1}$	-0.084		0.126^{***}		-0.089	
	(0.065)		(0.017)		(0.065)	
$Log\ assets_{f,t-1}$	-0.001		0.004^{***}		-0.001	
	(0.002)		(0.0005)		(0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{fkt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	-0.423^{***}	-0.613^{***}			-0.478^{***}	-0.740^{***}
	(0.104)	(0.128)			(0.106)	(0.139)
$dbr_{n,t-1}$: Demand-based risk			-0.225^{*}	-0.266^{**}	-0.328^{***}	-0.468^{***}
			(0.123)	(0.112)	(0.125)	(0.123)
$Tobin's\ Q_{f,t-1}$	0.070		0.074^{*}		0.074^{*}	
	(0.044)		(0.043)		(0.044)	
$Leverage_{f,t-1}$	-0.194^{***}		-0.186^{***}		-0.188^{***}	
	(0.044)		(0.044)		(0.044)	
$Debt\ coming\ due_{f,t-1}$	1.557^{***}		1.572^{***}		1.558^{***}	
	(0.251)		(0.249)		(0.252)	
$Average\ CDS_{f,t-1}$	-0.677^{**}		-0.631^{**}		-0.621^{**}	
	(0.262)		(0.263)		(0.264)	
$Log\ assets_{f,t-1}$	-0.070^{***}		-0.069^{***}		-0.069^{***}	
	(0.010)		(0.011)		(0.010)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	87.32	391.53	291.15	2511.36	563.71	366.22
Observations	132,991	132,991	132,991	132,991	132,991	132,991
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table reruns the baseline IV using only flows from retail mutual funds. The regression panel is at the firm-bond type-quarter level, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. The sample spans 2010 Q3 to 2023 Q4 and includes non-financial firms with at least \$1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The outcome variable is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's total assets in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. $issuance_{fnt}$, $cs^r_{fn,t-1}$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level.

Table F.4: Baseline IV using only flows from MFs

Panel A: First stage test for flow-based instruments						
	$cs^r_{fn,t-1}$		$dbr_{n,t-1}$		$cs^r_{fn,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{n,t-1}$: Exogenous net flows	−0.080***	−0.086***			−0.072***	−0.068***
	(0.007)	(0.008)			(0.007)	(0.008)
$z^{dbr}_{n,t-1}$			0.476***	0.559***	−0.050***	−0.105***
			(0.004)	(0.004)	(0.015)	(0.017)
$Tobin's\ Q_{f,t-1}$	−0.001		0.012***		−0.001	
	(0.011)		(0.003)		(0.011)	
$Leverage_{f,t-1}$	−0.007		0.014***		−0.006	
	(0.008)		(0.002)		(0.008)	
$Debt\ coming\ due_{f,t-1}$	−0.031		0.022*		−0.033	
	(0.046)		(0.012)		(0.046)	
$Average\ CDS_{f,t-1}$	−0.013		0.126***		−0.008	
	(0.065)		(0.017)		(0.066)	
$Log\ assets_{f,t-1}$	−0.001		0.004***		−0.001	
	(0.002)		(0.0005)		(0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{fnt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	−0.945**	−0.896**			−1.324***	−1.570***
	(0.377)	(0.384)			(0.461)	(0.560)
$dbr_{n,t-1}$: Demand-based risk			−0.224*	−0.265**	−0.507***	−0.690***
			(0.123)	(0.112)	(0.167)	(0.197)
$Tobin's\ Q_{f,t-1}$	0.069		0.074*		0.075	
	(0.047)		(0.043)		(0.051)	
$Leverage_{f,t-1}$	−0.198***		−0.186***		−0.191***	
	(0.045)		(0.044)		(0.045)	
$Debt\ coming\ due_{f,t-1}$	1.536***		1.571***		1.527***	
	(0.257)		(0.249)		(0.264)	
$Average\ CDS_{f,t-1}$	−0.680**		−0.630**		−0.596*	
	(0.284)		(0.263)		(0.316)	
$Log\ assets_{f,t-1}$	−0.070***		−0.069***		−0.069***	
	(0.010)		(0.011)		(0.010)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	15.3	70.25	290.43	2510.19	70.34	39.32
Observations	133,039	133,039	133,039	133,039	133,039	133,039
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table reruns the baseline IV using only flows from mutual funds. The regression panel is at the firm-bond type-quarter level, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. The sample spans 2010 Q3 to 2023 Q4 and includes non-financial firms with at least \$1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The outcome variable is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's total assets in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. $issuance_{fnt}$, $cs^r_{fn,t-1}$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

Table F.5: Baseline IV using only flows from insurers

Panel A: First stage test for flow-based instruments						
	$cs^r_{fn,t-1}$		$dbr_{n,t-1}$		$cs^r_{fn,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{n,t-1}$: Exogenous net flows	-0.381^{***}	-0.367^{***}			-0.383^{***}	-0.367^{***}
	(0.034)	(0.036)			(0.034)	(0.036)
$z^{dbr}_{n,t-1}$			0.476^{***}	0.559^{***}	-0.100^{***}	-0.148^{***}
			(0.004)	(0.004)	(0.014)	(0.016)
$Tobin's\ Q_{f,t-1}$	-0.001		0.012^{***}		-0.001	
	(0.011)		(0.003)		(0.011)	
$Leverage_{f,t-1}$	-0.008		0.014^{***}		-0.007	
	(0.008)		(0.002)		(0.008)	
$Debt\ coming\ due_{f,t-1}$	-0.034		0.022^{*}		-0.036	
	(0.046)		(0.012)		(0.046)	
$Average\ CDS_{f,t-1}$	-0.008		0.127^{***}		0.002	
	(0.065)		(0.017)		(0.065)	
$Log\ assets_{f,t-1}$	-0.001		0.004^{***}		-0.001	
	(0.002)		(0.0005)		(0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{fnt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	-0.685^{***}	-0.359			-0.658^{**}	-0.338
	(0.264)	(0.263)			(0.261)	(0.259)
$dbr_{n,t-1}$: Demand-based risk			-0.225^{*}	-0.266^{**}	-0.362^{***}	-0.355^{***}
			(0.123)	(0.112)	(0.129)	(0.129)
$Tobin's\ Q_{f,t-1}$	0.070		0.074^{*}		0.075^{*}	
	(0.045)		(0.043)		(0.045)	
$Leverage_{f,t-1}$	-0.196^{***}		-0.186^{***}		-0.188^{***}	
	(0.045)		(0.044)		(0.044)	
$Debt\ coming\ due_{f,t-1}$	1.547^{***}		1.571^{***}		1.550^{***}	
	(0.254)		(0.249)		(0.254)	
$Average\ CDS_{f,t-1}$	-0.677^{**}		-0.628^{**}		-0.613^{**}	
	(0.270)		(0.263)		(0.270)	
$Log\ assets_{f,t-1}$	-0.070^{***}		-0.069^{***}		-0.069^{***}	
	(0.010)		(0.011)		(0.010)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	24.93	136.3	290.26	2510.28	155.65	142.74
Observations	133,083	133,083	133,083	133,083	133,083	133,083
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table reruns the baseline IV using only flows from life and P&C insurers. The regression panel is at the firm-bond type-quarter level, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$. The sample spans 2010 Q3 to 2023 Q4 and includes non-financial firms with at least \$1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The outcome variable is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's total assets in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The instrument variables are constructed from Equation (26) and (31). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. $issuance_{fnt}$, $cs^r_{fn,t-1}$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

Table F.6: Natural disaster IV

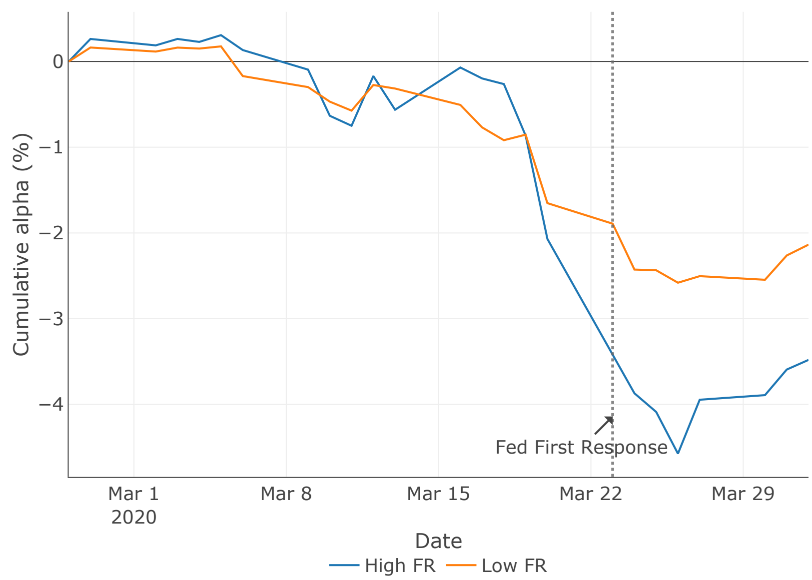
	$cs^r_{fn,t-1}$		$dbr_{k,t-1}$		$cs^r_{fn,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: First stage test for flow-based instruments						
$Exposure_{n,t-1}$: Exposure to disasters	0.170***	0.139***			0.170***	0.140***
	(0.029)	(0.031)			(0.029)	(0.031)
$z^{dbr}_{n,t-1}$			0.666***	0.834***	−0.098***	−0.075***
			(0.007)	(0.009)	(0.021)	(0.024)
$Tobin's\ Q_{f,t-1}$	−0.001		0.003		−0.001	
	(0.010)		(0.004)		(0.010)	
$Leverage_{f,t-1}$	−0.001		0.019***		−0.0005	
	(0.008)		(0.003)		(0.008)	
$Debt\ coming\ due_{f,t-1}$	−0.038		0.024		−0.040	
	(0.048)		(0.016)		(0.048)	
$Average\ CDS_{f,t-1}$	0.144*		0.222***		0.149*	
	(0.077)		(0.027)		(0.077)	
$Log\ assets_{f,t-1}$	−0.001		−0.0003		−0.001	
	(0.002)		(0.001)		(0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{fnt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fn,t-1}$: Relative credit spread	−1.226**	−2.212**			−1.147*	−2.207**
	(0.620)	(0.955)			(0.603)	(0.953)
$dbr_{n,t-1}$: Demand-based risk			−0.497***	−0.512***	−0.664***	−0.707***
			(0.154)	(0.127)	(0.191)	(0.180)
$Tobin's\ Q_{f,t-1}$	0.027		0.029		0.029	
	(0.048)		(0.046)		(0.048)	
$Leverage_{f,t-1}$	−0.148**		−0.134**		−0.131**	
	(0.061)		(0.060)		(0.062)	
$Debt\ coming\ due_{f,t-1}$	1.470***		1.524***		1.481***	
	(0.329)		(0.322)		(0.329)	
$Average\ CDS_{f,t-1}$	0.084		0.034		0.243	
	(0.413)		(0.341)		(0.418)	
$Log\ assets_{f,t-1}$	−0.066***		−0.066***		−0.067***	
	(0.013)		(0.013)		(0.013)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	6.72	36.43	174.61	1385.36	41.95	36.45
Observations	57,774	57,774	57,774	57,774	57,774	57,774
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the results of the natural disaster IV. The regression panel is at the firm-bond type-quarter level from 2010 Q3 to 2023 Q4, conditional on bond types with positive amounts outstanding at any point over the prior one year from t to $t-3$, and the top 10 bond types with the highest historical exposure to natural disasters and their neighbors. We include non-financial firms with at least $1 million in total assets and book values, and with bonds that have at least one year of remaining maturity. The outcome variable is the amount issued for a given bond type n by firm f in period t, percentage normalized by the firm's total assets in the prior period. The endogenous variables are constructed from Equation (27) and (**??**). The endogenous variable, relative credit spreads, is constructed from Equation (27). The instrument variable for cs^r_{fnt}, bond-type specific exposure to natural disasters, follows the methodology of Ge (2022); and the instrument for dbr_{nt} is constructed from Equation (31). The firm-level controls include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize $issuance_{fnt}$, $cs^r_{fn,t-1}$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level.

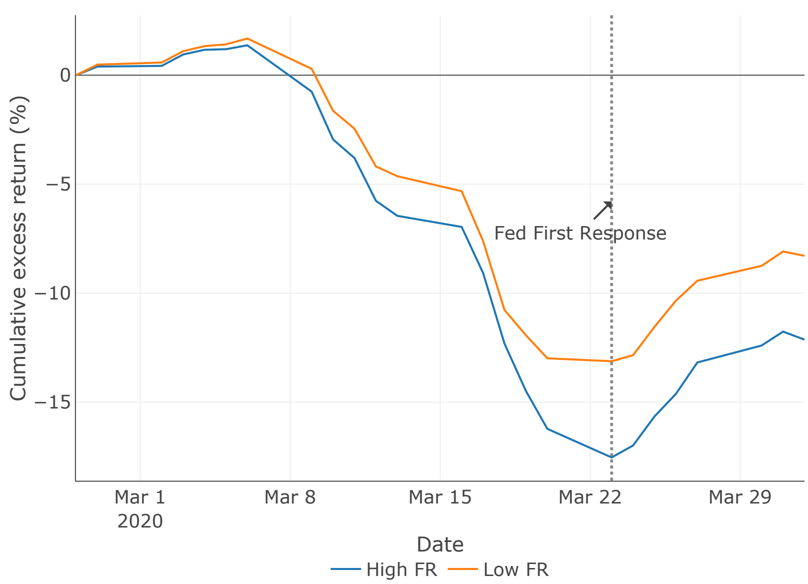
G Impact of funding risk in times of distress

Figure G.1: Corporate bond portfolio returns during COVID: High FR vs. Low FR

a. Cumulative abnormal returns



b. Cumulative excess returns



Note: This figure presents the daily cumulative returns of corporate bond portfolios during the COVID-19 outbreak in March 2020. The portfolios include all BBB-rated corporate bonds with time-to-maturity between 3 and 10 years, categorized into high and low funding risk (FR) portfolios based on median funding risk. In Figure (b), portfolio excess returns are calculated as the average daily excess returns of the bonds, weighted by their notional amounts outstanding. In Figure (a), daily returns are regressed on the market returns and term factors, and we plot the cumulative sum of residuals.

H Firm sophistication and underwriters

In practice, broker-dealers that underwrite bonds advise firms on investor demands and market conditions as firms decide how to raise capital. We find that firms that interact with more unique underwriters in the recent past tend to have a more widely dispersed investor base. Specifically, we regress the measure of funding risk on a measure of the number of unique underwriters that the firm has hired for bond issuances in the past five years. We control for the age of the firm, investment opportunities, leverage, average CDS, the debt coming due, and the size of the firm.

$$\begin{aligned} Funding\_Risk_{ft} = {} & \beta \# Underwriters_{ft} + \gamma_1 Age_{ft} + \gamma_2 TobinsQ_{ft} + \gamma_3 Leverage_{ft} \\ & + \gamma_4 AvgCDS_{ft} + \gamma_5 DebtDue_{ft} + \gamma_5 TotalAssets_{ft} + \alpha_f + \alpha_t + \varepsilon_{ft} \end{aligned} \tag{76}$$

See Table H.1 for the results. Having more unique underwriters advising the firm is positively correlated with dispersion across investors. This is true with firm and month fixed effects, thus holds both in the cross section and in the time series. Increasing the number of underwriters used in the past five years by 5 will reduce funding risk by about 5% of one standard deviation.

Table H.1: Underwriter analysis

	Dependent variable:			
	Number of unique bond-types		Funding risk	
	(1)	(2)	(3)	(4)
Number of unique underwriters	0.103***	0.107***	−0.004***	−0.004***
	(0.002)	(0.002)	(0.0004)	(0.0004)
Firm age	−0.015***	0.027	−0.013***	−0.036**
	(0.002)	(0.061)	(0.0005)	(0.015)
Tobin's Q	−0.002	−0.002	0.002***	0.002***
	(0.002)	(0.002)	(0.0005)	(0.0005)
Leverage	1.805***	1.406***	−0.514***	−0.549***
	(0.099)	(0.101)	(0.026)	(0.025)
Average CDS	−0.015**	0.006	−0.032***	−0.022***
	(0.006)	(0.006)	(0.001)	(0.002)
Debt coming due	0.685	0.536	−0.261	−0.520***
	(0.639)	(0.635)	(0.166)	(0.160)
Total assets (log)	0.813***	0.816***	−0.053***	−0.060***
	(0.023)	(0.023)	(0.006)	(0.006)
Quarter FE	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	33,568	33,568	33,530	33,530
R^2	0.855	0.858	0.684	0.710
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the impact of the number of unique underwriters that the firm hired for bond issues on its level of financial sophistication. The sample is quarterly from 2003 Q1 to 2023 Q4, based on FISD, Compustat and eMAXX data. The outcome variables are (1) the number of unique bond types that the firm held in that quarter, and (2) the funding risk of the firm in that quarter. The independent variable is the number of unique underwriters that the firm has hired for bond issues in the past five years. The contemporaneous firm-wide controls include the age of the firm, Tobin's Q, leverage, average CDS, debt coming due, and the size of the firm. We winsorize all variables at 1% and 99% to remove outliers.

I Define demand-based risk and funding risk

I.1 Define funding risk

A firm's funding risk is computed as its weighted exposure to demand-based risk based on its outstanding bond types:

$$FR_{ft} = \sqrt{\underbrace{q_{ft}}_{1 \times N} \underbrace{\Sigma_t}_{N \times N} \underbrace{q_{ft}}_{N \times 1}} \tag{77}$$

where q_{ft} is a $N \times 1$ vector of the par amount firm f has outstanding on bond n, normalized by its contemporaneous total assets:

$$\underbrace{q_{ft}}_{N \times 1} = \begin{bmatrix} \frac{amtout_{1ft}}{assets_{ft}} \\ \vdots \\ \frac{amtout_{Nft}}{assets_{ft}} \end{bmatrix} \tag{78}$$