

Financially Sophisticated Firms

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Abstract

Using comprehensive new data on firms, bond issuance, and portfolio holdings, we show that firms strategically choose their bond structures to simultaneously reduce their cost of capital and mitigate "financial fragility"—their exposure to investor demand shocks. By tailoring bonds to specific investor preferences, firms shape their bondholder composition and thereby manage their exposure to demand-based risks. Firms value low exposure to demand-based risk because it enhances resilience to credit shocks and creates firm value. However, because bonds with low demand risk trade at a discount, firms face a fundamental trade-off: they must choose between minimizing their cost of capital and reducing financial fragility. Our findings bridge asset pricing and corporate finance by demonstrating how bond supply endogenously responds to investor demand patterns.

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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. While the corporate finance literature explains the variation in debt types 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. This creates a tradeoff: while catering to demand can reduce firms' cost of capital through higher bond prices, it also exposes firms to idiosyncratic demand shocks. Consequently, firms have incentives to diversify their investor base. We show that firms choose to issue bond types that increase firm value either by reducing the cost of capital or by mitigating financial fragility.

Our contribution is to provide evidence of this dual role of market timing in bond issuance. First, we show that prices of a given bond type are affected by idiosyncratic shocks to the investors that hold that bond type. Furthermore, this demand-driven price increase leads firms to issue more of that bond type. The magnitudes are significant: one standard deviation reduction in credit spreads driven by idiosyncratic investor demand shocks increases firms' issuance by 18% of the median conditional quarterly issuance for that bond type, corresponding to an increase of approximately \$156 million. This is novel evidence of firms catering to investor demand for specific bond characteristics.

However, optimizing bond structure involves a second crucial dimension: managing *financial fragility*, which represents a firm's exposure to investor demand shocks that could disrupt access to credit markets. Using an instrumental variable analysis, we demonstrate that firms prefer to issue bonds with lower *demand-based risk* (*dbr*), our bond-level measure of the exposure to idiosyncratic investor shocks.¹ Firms value bonds with low *dbr* because it decreases their financial fragility, which translates into greater resilience to aggregate credit market shocks. This does not come for free: bonds with lower *dbr* on average trade at lower prices, forcing firms to make a tradeoff between lower costs of capital and lower demand-based risk.

Our findings bridge traditional asset pricing and corporate finance models by highlighting that asset supply is endogenous to investors' demand, and it is not perfectly elastic. The complexity of

¹This measure is similar in spirit to the stock price fragility measure in Greenwood and Thesmar (2011), but we define *dbr* at the bond level, allowing firms' bond portfolios to determine their aggregate exposure to demand-based risk. Therefore, fragility in our setting is not exogenous, but it is endogenous to firms' capital-structure decisions.

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 intermediaries, 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)).

Central to understanding this financially sophisticated behavior is recognizing that firms have strong incentives to diversify their investor base to mitigate financial fragility. Previous literature shows that bond investors have differing preferences (Bretscher et al. (2022), Jansen (2025)), and the institutional structure of those investors may impact the firm’s bond prices (Coppola (2022), Chodorow-Reich et al. (2020)). Firms can then effectively choose their investor composition by choosing which bonds to issue. As such, a diversification incentive emerges because firms relying heavily on a narrow set of investors become vulnerable to idiosyncratic shocks affecting those specific investors—such as wealth declines or portfolio rebalancing needs—that can depress bond prices and restrict access to credit markets. By issuing multiple bond types that appeal to different investor segments, firms can hedge against these demand shocks. This strategy proves particularly valuable because market frictions impede a firm’s ability to quickly adjust funding sources, especially during distress periods when external capital is most critically needed. For example, Zhu (2021) and Barbosa and Ozdagli (2021) show that intermediaries tend to lend to firms whose bonds they already hold, particularly during stressed market conditions. Furthermore, when prices decline, investors might not be able to distinguish between fundamental firm deterioration and temporary liquidity shocks. Consequently, the prices of outstanding bonds directly impact firms’ cost of financing, which justifies firms’ concern with financial fragility. As one example of this diversification approach, Ford Motor Co. emphasizes in its investor presentations that it maintains funding “diversified across platforms and markets” (see Figure C.1).

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 portfolio holdings data. Second, we present a model that illustrates the incentives for firms to engage in financial sophistication. Finally, we test the predictions of this model, documenting and quantifying financial sophistication

²Catering in corporate bond markets extends beyond equity versus bonds (e.g., Baker and Wurgler (2004), (Baker (2009)), Ma (2019)) or variations in maturity structure (e.g., Greenwood et al. (2010)).

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 bond type classification, we document two novel facts. First, a significant portion of firms in our sample have complex bond structures: 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 can affect a firm’s external finance costs, firms are motivated to diversify their demand based risk — a point we will later support with empirical evidence.

Motivated by these findings, we present a theoretical model to illustrate the mechanism driving 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 constrained by short-selling and borrowing limitations. Firms strategically optimize their capital structure by considering both the demand curve for specific bonds and their financial fragility. By tailoring cash flow structures, firms can create assets that align with investor demand, thereby reducing their cost of capital. However, the incentive to issue high-priced bonds is tempered by the associated exposure to demand-based risk. Following the literature, we model the cost of issuing bonds as a quadratic cost function reflecting the reduced-form expense of external funding. Our approach differs in that this cost depends on asset-specific risks, crucially including those stemming from investors' idiosyncratic shocks. Consequently, asset supply in our model is endogenously determined by value-maximizing firms rather than being exogenously fixed, as commonly assumed in asset pricing models.

Although our model takes heterogeneous demand as exogenous, it is not difficult to find micro-foundations for this heterogeneous demand that arise from motives beyond hedging. Heterogeneous demand shocks can stem from differing institutional constraints. For instance, U.S. insurers, who hold roughly one-quarter of the U.S. corporate bond market, are bound by risk-based capital requirements and face significant long-term liability exposures (Becker and Ivashina (2015), Kojien and Yogo (2022), Sen (2023)), which shape their preference for long-term, safer assets. 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)). All these institutional motives generate specific demands for particular bond characteristics to which firms can respond.

The model yields four empirically testable hypotheses. First, shocks to investors' wealth or hedging preferences affect equilibrium bond prices. The second and third hypotheses concern financially sophisticated firm behavior: firms strategically adjust their debt structure by issuing more bonds that either (1) trade at higher prices (lower credit spreads) or (2) reduce demand-based risk. Our fourth hypothesis predicts that demand-based risk is priced in the cross-section of corporate bond returns. To demonstrate that the main forces of our model are operative, we also show that firms with bond portfolios exhibiting lower demand-based risk have greater resilience to aggregate bond market shocks and that 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 or preference shocks affect prices. An ideal instrument would resemble that used in Ge and Weisbach (2021), where hurricanes cause substantial losses for certain property insurers, compelling them to sell bonds from their portfolios. Such forced sales would increase the credit spreads of these bonds relative to comparable bonds not held by the insurers, and alter the demand-based risks through changes in asset-holding shares. Since this variation is plausibly orthogonal to firms' issuance decisions, it would serve as a valid instrument. However, because hurricanes typically impact only a limited number of investors, we instead develop two broader instruments based on mutual fund flows and insurers' operating income variation for our baseline instrumental variable analysis. Specifically, we orthogonalize fund flows (for mutual funds) and operating income growth (for insurers) with contemporaneous portfolio returns and value-weighted time fixed effects. Our identification hypothesis is that the residual flows cause variation in equilibrium credit spreads, 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 (Kojien and Yogo (2019), Gabaix and Kojien (2021)), which demonstrates that asset prices are highly inelastic compared to traditional models, allowing flows to significantly 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 18% of the median conditional quarterly issuance for that bond type. Our results show that firms are price elastic in choosing bond capital structure.

Third, we find that financially sophisticated firms actively reduce fragility 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 2% of median quarterly conditional net issuance of a given bond type. 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 (consistent with the fourth prediction of our model). 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 reduce their exposure to demand-based risk.

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 leads 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 for a subset of assets with significant property insurer holdings, following Ge and Weisbach (2021) and Ge (2022), and find a similar firm issuance response to credit spreads and demand-based risk.

To support our model's assumption, we examine how firms' diversification strategies translate into measurable resilience benefits. We compute a firm's demand-based risk as its exposure to investors' non-fundamental idiosyncratic shocks by aggregating the demand-based risks of the firm's outstanding bonds. Because investors differ in their bond holdings, there is significant variation in firms' exposure to demand-based risk depending on their outstanding bond portfolio composition. We show that firms with low demand-based risk also exhibit lower return volatility in their overall bond portfolios, consistent with diversification benefits. We then examine the relationship between a firm's demand-based risk and its resilience to credit market shocks, measured by its CDS beta relative to the aggregate CDX market. Our findings reveal that as firms diversify their investor base and reduce demand-based risk, their credit market beta declines, indicating increased resilience. Specifically, a one-standard deviation decrease in demand-based risk corresponds to a

nearly 6% reduction in a firm's CDS beta relative to the mean.

Furthermore, to show that firms optimize their value by selecting bonds to issue, we provide evidence that firms create value through financially sophisticated behavior without increasing financial distress risk. Using event study analyses of two-day returns around bond issuance, we show that issuing bond types with lower relative credit spreads increases both shareholder value and enterprise value while not significantly affecting the firm's CDS spreads (a common market-based measure of default risk). Conversely, issuing bond types with lower *dbt* reduces the firm's CDS spreads upon issuance without negatively impacting equity value. In terms of magnitudes, issuing a relatively more expensive bond type generates a net positive two-day abnormal return of 2.7 basis points. A trading strategy that exploits financially sophisticated issuance timing yields an abnormal annualized return of approximately 3.5%. We interpret these results as evidence that financial sophistication creates firm value without increasing distress risk.

We provide additional tests to validate our key mechanisms. First, we find evidence that firms are less likely to attract new investors when experiencing financial distress. This finding supports the value of diversifying credit supply during normal periods to maintain access to a broader lender base during stressed conditions. Second, we document that investors who previously held large positions in a given bond type disproportionately increase their holdings following new issuance of that same type. This pattern runs counter to portfolio diversification motives, instead supporting our view that market frictions, including short-selling constraints, create scarcity for certain bond types. Consequently, firms play a pivotal role as suppliers of specific assets that cannot be easily replicated by intermediaries, allowing them to strategically influence asset supply and pricing.

This paper contributes primarily to four strands of literature. First, we add to the literature on how corporate capital structure decisions depend on market conditions. Erel et al. (2012) and Begenu and Salomao (2019) show how capital structure depends on the business cycle. Several market timing papers show evidence that capital structure respond to asset prices: 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 interest 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. Thus, market timing arises from firms catering to commonly known demand shocks and does not depend on private information. Our second key innovation is to recognize that, 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.³ We 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.⁴ 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 bond 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. Firms share the role of intermediaries, who engineer securities to match investor preferences (Gennaioli et al. (2010), C  l  rier and Vall  e (2017), Lugo (2021), De Jong et al. (2013)) or pool and tranche assets to mitigate informational frictions (Allen and Gale (2004); DeMarzo (2005)).⁵ Closely related to our paper is Bisin et al. (2014), who model capital structure with incomplete markets and hedging

³There is an analogous concept of holdings-driven fragility in stocks (Friberg et al. (2024); Greenwood and Thesmar (2011)). The difference in our paper is that fragility is not exogenous, instead firms actively manage their fragility through their capital structure decisions.

⁴If interested, please check the authors' websites.

⁵A related strand examines household financial sophistication. For instance, Calvet et al. (2009) measure underdiversification, risky-share inertia, and the disposition effect.

demand. Our contribution is to show that investor-driven heterogeneity, e.g., 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. Examining corporate financial sophistication is particularly important because non-bank intermediaries are increasingly dominating markets (Buchak et al. (2024)), which changes 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 (e.g. Kojien and Yogo (2019), Vayanos and Vila (2021), Bretscher et al. (2022), Jansen (2025)). 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 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 that support our model mechanism, and Section 6 concludes the paper.

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 bond issuers in FISD, and the match can change over time as companies merge, go through bankruptcy, or spin off subsidiaries. Moreover, the names or CUSIPS of subsidiaries that issue bonds may look very different from the identifiers

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 using the WRDS bond link, which is commonly used in the literature. We then supplement this merge with several other data sources, string matching, and manual matching where needed. We verify our merge, described in detail in Appendix A, 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.⁶

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, CDS price data from Markit, and stock price from CRSP. We exclude bonds with less than one-year time-to-maturity, and exclude floating and convertible bonds due to a lack of pricing data. The firm-bond final dataset includes 22,953 unique bonds issued by 2,459 firms from 2000 Q1 to 2023 Q4.

Bond issuers are not representative of the entire corporate sector. The median bond issuer in our sample has \$18.3 billion in total assets and \$5.7 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. Figures C.3 and C.4 show the number of unique firms and corporate bonds in both our full sample and baseline analysis as they change over time.

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

⁶See Appendix A for more details on the merge method and results.

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 than 10 years is 95% or more across time, otherwise, they are classified as Long funds.⁷ Note that CRSP provides consistent corporate bond holdings data for most mutual funds only starting in 2010 Q3, so we restrict the sample for our main analysis 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 C.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 B) and portfolio allocation (Panel C) for each investor category.⁸ We compute mutual fund flows using returns and assets under management (AUM) from CRSP. We compute insurer flows using year-over-year changes in quarterly operating income from NAIC, which accounts for seasonality. The detailed construction of our exogenous flow measures is provided in Section 4.2.

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.⁹

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

⁷See Panel A of Table 1 for the detailed classification of six investor categories.

⁸See Appendix Table C.1 for the share of corporate bonds outstanding held by each investor category.

⁹Please refer to Figure C.2 in the Appendix for more details.

of the firm's history, which includes consolidations, acquisitions, and spin-offs. However, even on a given issuance day, firms may issue many bond types simultaneously. 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).¹⁰ 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 B.1 in the Appendix reports the distribution of the average number of unique 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 2.¹¹ 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. 23% of all firms in

¹⁰We use the combination of Standard & Poor's, Moody's, and Fitch credit ratings.

¹¹Rauh 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.

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 C.2 in the Internet 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.

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), 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.

One implication of this mapping is that one way firms have to diversify across different investors is by issuing multiple bonds. Figure 4 shows 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. Thus, the more bond types a firm has outstanding, the more investors hold its bonds.

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 10y+). 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. We then plot the cumulative returns of these two portfolios in Figure 5.

A striking picture emerges from this exercise: portfolios with high exposure to mutual funds holdings have -90% negative correlation with portfolios with high exposure to insurers holdings. This strong negative correlation, especially in times of distress, means that firms that have bond structures exposed to both portfolios can diversify specific sector idiosyncratic shocks, thereby potentially minimizing the cost of financial distress. When a firm is hit by an adverse shock and needs to raise capital, the firm is better off if it can draw on a broader, more diversified investor base.

What might drive the negative correlation between mutual funds and insurer corporate bond portfolios? The literature documents that insurers, given their long-term liabilities, are less likely to sell bonds during downturns (Chodorow-Reich et al. (2020), O'Hara et al. (2022), Coppola (2021)). We argue that mutual funds can also serve as "safe hands," providing valuable diversification across investor types. For example, when insurers face regulatory pressure to sell bonds following credit downgrades, mutual funds can help preserve firms' credit access. To test this mechanism, we conduct an event study in the internet appendix, tracking average firm-level credit spreads around downgrades from A to BBB ratings. Firms with higher mutual fund ownership shares before downgrade experience smaller increases in credit spreads afterward, suggesting that diversifying bondholder composition between mutual funds and insurers creates meaningful benefits for corporate borrowers.

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 illustrates how a profit-maximizing firm will

optimally choose a complex debt structure catering to heterogeneous 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 can 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), a firm’s choice of debt structure has a crucial role in determining the supply of such assets, thereby directly affecting equilibrium prices and the firm’s overall cost of capital. On the other hand, through the same mechanism, idiosyncratic shocks to investors’ hedging demand (either wealth or preferences) impact asset prices, exposing firms’ outstanding bonds to investor demand shocks. Because these shocks can impact refinancing costs, we assume that firms dislike volatility in their outstanding bonds as it affects their financial fragility. In our model, optimal capital structure choice resembles a portfolio allocation problem, in which firms trade off the financing costs and financial fragility.

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. All proofs are in the Internet Appendix D.

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 issued at par (price = 1) and one risk-free saving technology in perfectly elastic supply with interest rates normalized to zero. Each risky asset n has random gross return $R(n)$, and excess

return $\mathbf{r} = \mathbf{R} - \mathbf{1}$. 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, $\mathbf{f} \in \mathbb{R}^{K_r}$, such that for each asset n

$$r_{t+1}(n) = \mu_t(n) + \boldsymbol{\beta}_t(n)^\top \mathbf{f}_{t+1} + \epsilon_{t+1}^r(n), \quad (1)$$

where $\mathbb{E}_t[\mathbf{f}_{t+1}] = \mathbf{0}$, $\mathbb{E}_t[\epsilon_{t+1}^r] = \mathbf{0}$, $\text{Var}_t(\mathbf{R}) = \Sigma_{rt} = \boldsymbol{\beta}_t^\top \Sigma_f \boldsymbol{\beta}_t + \Sigma_{\epsilon_r t}$, $\text{Var}_t(\mathbf{f}) = \Sigma_{f,t}$, and $\text{Var}_t(\epsilon_{t+1}^r) = \Sigma_{\epsilon_r} = \text{diag}(\boldsymbol{\sigma}_{\epsilon_r}^2)$.

3.2 Investors

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 \mathbf{f}_{t+1} . Let ω_{it}^f and ω_{it} be the portfolio weights on the risk-free assets and the risky assets, respectively. The next-period wealth, W_{it+1} , is:

$$W_{it+1} = W_{it} [\omega_{it}^f + \boldsymbol{\omega}_{it}^\top \mathbf{R}_{t+1} - \boldsymbol{\theta}_{it+1}^\top \mathbf{f}_{t+1}]. \quad (2)$$

Agents have mean-variance indirect utility over wealth in period $t + 1$ with a risk aversion parameter γ_i . Since the agent's problem is essentially static, we drop the time subscripts while solving the model, 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. Thus, agents solve:

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

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

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

We define $\mathbf{h} = \text{Cov}(\mathbf{R}, \mathbf{f}) \in \mathbb{R}^{N \times K_r}$ as the covariance of returns and factors, and Lagrange multipliers $\lambda_i \geq 0$ for the short-selling constraints $\boldsymbol{\omega}_i \geq \mathbf{0}$, and $\lambda_{if} \geq 0$ for the borrowing constraint $\mathbf{1}^\top \boldsymbol{\omega}_i \leq 1$.

From the investors' first order condition, the optimal portfolio choice is

$$\boldsymbol{\omega}_i^* = \frac{1}{\gamma_i W_{i0}} \Sigma_r^{-1} \left[\boldsymbol{\mu} + \gamma_i W_{i0} \mathbf{h} \boldsymbol{\theta}_i + \frac{1}{W_{i0}} (\lambda_i - \lambda_{if} \mathbf{1}) \right] \quad (6)$$

We can use the factor structure of returns to write the optimal portfolio choice for each asset n as a linear function of expected returns, hedging demand, and the Lagrange multipliers as:

$$\omega_i^*(n) = \frac{1}{\gamma_i W_{i0} \sigma_{\epsilon_r}(n)} \left[\mu(n) - \kappa_i \boldsymbol{\beta}^\top(n) + \gamma_i W_{i0} \boldsymbol{\theta}_i \mathbf{h}(n) + \frac{1}{W_{i0}} (\lambda_i(n) - \lambda_{if}) \right] \quad (7)$$

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

3.3 Firm

There is also a representative firm that takes bond prices and investors' 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 there is no uncertainty about the firm's payoff D , the 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 $\mathbf{q}^\top \mathbf{1}$, where $\mathbf{q} \in \mathbb{R}^N$ represents the vector of issuance quantities across all bonds. Each bond n tracks different projects and therefore has specific risk characteristics that map to the factor structure in equation (1).

The firm also recognizes costs associated with each bond type n . This cost comprises two components: investor demand shocks and other bond-specific issuance costs. 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 convex bond-issuance costs resemble the typical reduced-form convex costs in corporate finance models. The innovation in our setting is that we make this financing cost dependent on the risk coming from investors' idiosyncratic demand.¹² The investor demand shocks correspond to either preference shocks (θ_{it}) or wealth shocks (W_{it}).

Let $\iota_t(n)$ denote the shocks driving the cost of external finance of issuing each bond n . We assume there are K_ι factors, $\mathbf{g}_t \in \mathbb{R}^{K_\iota}$, driving investor demand and a $\epsilon_{it}(n)$ an idiosyncratic cost.

¹²We model demand-based 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, asymmetric information or mismatched payoffs between assets and liabilities.

The random cost of each bond n can be expressed as

$$\iota_{t+1}(n) = \bar{\iota}(n) + \delta_t^\top(n) \mathbf{g}_{t+1} + \epsilon_{\iota_{t+1}}(n) \quad (8)$$

where $\mathbb{E}_t[\mathbf{g}_{t+1}] = \mathbf{0}$, $\mathbb{E}_t[\epsilon_{\iota_{t+1}}] = 0$, $Var_t(\iota_t) = \Sigma_{\iota_t}$, $Var_t(\mathbf{g}_{t+1}) = \Sigma_{g_t}$, and $Var_t(\epsilon_{\iota_{t+1}}) = \Sigma_{\epsilon_{\iota_t}} = \text{diag}(\sigma_{\epsilon_t}^2)$.

The firm's objective is to determine the optimal financing strategy by maximizing financing efficiency while managing demand-based risk. Let $\gamma_f > 0$ be the firm's cost of choosing different bonds. It chooses its debt structure to maximize

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

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

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

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 to make sure that firms cannot buy back their own bonds. We will assume this is not binding by imposing a large enough hedging demand from the investors' problem.¹³ The third 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 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.

From the firm's first-order condition, the optimal issuance decision is:

$$\mathbf{q}_s^* = \frac{1}{\gamma_f} \Sigma_t^{-1} (\mathbf{1} - \mathbb{E}[\mathbf{R}]) = -\frac{1}{\gamma_f} \Sigma_t^{-1} \boldsymbol{\mu}, \quad (12)$$

¹³In the model, firms issue risky bonds only when credit spreads are negative. While this may seem counterintuitive, negative spreads arise because investors are willing to pay a hedging premium for securities that offer cash flows that hedge their background risk. This result stems from the model's assumption that the firm's outside option is risk-free debt. In reality, however, firms undertake risky projects, and since investors are rational and risk-averse, the outside option would typically involve issuing bonds with positive credit spreads.

where $\boldsymbol{\mu} = \mathbb{E}[\mathbf{R}] - \mathbf{1}$ is an expected (excess) return and Σ_t represents the demand-based 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 :

$$q_s^*(n) = -\frac{1}{\gamma_f \sigma_{\epsilon_t}^2(n)} \left[\boldsymbol{\mu}(n) - \boldsymbol{\delta}^\top(n) \boldsymbol{\kappa}_f \right] \quad (13)$$

where $\boldsymbol{\kappa}_f = D_t \boldsymbol{\delta} \Sigma_{\epsilon_t}^{-1} \boldsymbol{\mu}$, a $K_t \times 1$ vector that is importantly constant across assets and $D_t = \left(\Sigma_g^{-1} + \delta \Sigma_{\epsilon_t}^{-1} \delta^\top \right)^{-1}$

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.

3.4 Equilibrium

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 :

$$q_s^*(n) = \sum_i q_i^*(n) \quad \forall n \quad (14)$$

We first write the aggregate demand for each asset n as:

$$q_d^*(n) = \frac{W_0}{\gamma_d \sigma_{\epsilon_r}^2(n)} \left[\boldsymbol{\mu}(n) + \gamma_d \mathbf{h}(n) \bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}}(n) - \boldsymbol{\beta}^\top(n) \bar{\boldsymbol{\kappa}} \right] \quad (15)$$

where $W_0 = \sum_i W_{0i}$ is the total investable wealth in the economy.

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:

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

where $\tilde{w}_i = \frac{W_{0i}}{W_0}$ 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, $\bar{\boldsymbol{\lambda}} = \frac{1}{W_0} \sum_i \tilde{\boldsymbol{\lambda}}_i$

is the $N \times 1$ economy-wide tightness trading constraints per unit of wealth, and $\bar{\kappa} = \sum_i \tilde{w}_i \kappa_i$ 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 :

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

where

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

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

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

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

$$B_\delta(n) = A(n) \cdot \frac{1}{\gamma_f \sigma_i^2(n)} \kappa_f \quad (22)$$

Note that if γ_f goes to 0, the firm is unconcerned with financial fragility, then the firm could supply infinitely many bonds with higher prices 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.

If markets were complete, trading unconstrained, and issuance costless, 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 make the realistic assumption that the firm uniquely holds the ability to issue financial securities with certain 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. There exists an optimal capital structure decision in which firms trade off the proceeds from issuance and financial fragility.

3.5 Predictions

Prediction 1: Investors' hedging needs affect equilibrium prices. Our first hypothesis is that idiosyncratic shocks to wealth (W_{it}) or preferences (θ_{it}) 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:

$$\nabla_{\bar{\theta}} \mu = - \left(\frac{1}{\gamma_f} \Sigma_t^{-1} + \frac{W_0}{\gamma_d} \Sigma_r \right)^{-1} \cdot \frac{W_0}{\gamma_d} \Sigma_r \cdot \mathbf{h} \quad (23)$$

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

Prediction 2: Prices affect bond supply. Conditional on demand-based risk, δ , firms will issue more bond types that have lower expected excess returns. This is easy to see from Equation 12:

$$\forall m, n \quad s.t. \quad \mu(m) > \mu(n) \mid \delta(n) = \delta(m) \implies q^S(m) < q^S(n)$$

Prediction 3: Demand-based risk affects bond supply. Conditional on prices, firms will issue more bonds with lower demand-based risk. This is also easy to see from Equation 12, as $\kappa_f < 0$:

$$\forall m, n \quad s.t. \quad \delta(m) > \delta(n) \mid \mu(m) = \mu(n) \implies q^S(m) < q^S(n)$$

Prediction 4: Demand-based risk affects the cross-section of asset prices. In the cross-section of bonds, bonds with higher demand-based risk δ also have lower yields and/or higher prices. This is clear from Equation 17, where the coefficient on δ in the equilibrium expected return equation is $B_\delta(n) < 0$ (because $\kappa_f < 0$, while the other terms entering into the coefficient are positive). Notice this is at the heart of the firm's trade-off when deciding which bonds to issue: since assets with lower dbr have lower prices, they must trade-off between maximizing proceeds for this issuance versus reducing their financial fragility going forward.

4 Empirical tests of the model predictions

This section presents empirical tests of our model’s key predictions using exogenous demand shocks that affect bond prices while remaining orthogonal to firms’ financing fundamentals. Our identification strategy requires isolating pure wealth shocks to large investors that are unrelated to firm-level investment or borrowing decisions.

To illustrate the ideal instrument, consider a hurricane that strikes a region distant from our sample firms but inflicts substantial losses on property insurers. These insurers are forced to liquidate their fixed portfolios (e.g., 70% in bond type A, 30% in type B) to meet claims. This mechanical fire-sale would increase the credit spread of bond A relative to bond B (Hypothesis 1), and our model predicts firms should respond by reducing issuance of A bonds relative to bond B (Hypothesis 2). However, if bonds held by property insurers exhibit low demand-based risk relative to other bonds—perhaps because property insurers have lower systematic flows—then the relative increase in type B issuance would be attenuated due to demand risk considerations (Hypothesis 3). The key insight is that hurricanes are exogenous events, making the resulting insurer operating losses plausibly orthogonal to unobserved firm characteristics affecting issuance decisions. Thus it is a valid instrument for testing strategic capital structure rebalancing by financially sophisticated firms.

We validate this approach using insurer fire-sale instruments following the methods of Ge and Weisbach (2021) and Ge (2022) in Internet Appendix E.5. However, this analysis focuses on the ten bond types with the greatest insurer holdings to ensure relevance. To demonstrate the breadth of our findings across the full spectrum of bond types, our main analysis instead exploits quarter-to-quarter variation in investment flows into mutual funds and insurance companies. We residualize these flows for contemporaneous returns to create orthogonalized instruments for both relative yields and demand-based risk. This approach delivers a broader test of how prices and idiosyncratic demand risk drive firms’ strategic issuance decisions.

4.1 Defining key variables

Before testing the hypotheses, we define our key variables. We define how we construct bond yields (μ in the model), investor demand shocks (W_i or θ_i in the model), and demand-based risk (δ in the model). The distribution of our key variables included in our regression analyses is reported in Table 4.

4.1.1 Prices

We define a proxy for yield at the bond type level. We construct a firm-specific relative credit spread for bond type n that excludes firm f 's own issuances. This exclusion better approximates the market-wide price of a given bond type and avoids potential bias from overrepresentation by the firm's own bonds.

$$cs_{fnt}^r = \left(\frac{\overline{cs}_{nt,-f} - \overline{cs}_{t,-f}}{\overline{cs}_{t,-f}} \right) - \frac{1}{12} \sum_{\tau=t-12}^{t-1} \left(\frac{\overline{cs}_{n\tau,-f} - \overline{cs}_{\tau,-f}}{\overline{cs}_{\tau,-f}} \right) \quad (24)$$

where credit spreads on the right-hand side represent averages at the bond type-month level, weighted by bonds outstanding in the same period. The measure cs_{fnt}^r captures the deviation of bond type n 's credit spread relative to other outstanding bonds in period t .

Since different bond types typically exhibit systematically different credit spread levels, we demean the price deviation measure using its average over the preceding 12 months. Higher values of cs_{fnt}^r correspond to relatively higher credit spreads and thus lower bond prices compared to its long-run norm. Our measure of relative credit spreads can also be interpreted as a long-term change in credit spreads, which is what firms likely respond to when selecting when to issue specific bond types. Unlike investors, who can react to short-term price swings by trading in and out of their positions, firms (even if they can issue quickly) cannot always cost-effectively buy back bonds once issued. As a result, firm issuance choices more likely reflect price deviations from each bond type's long-run average.

4.1.2 Demand shocks

To construct measures for investor demand shocks that arise from changes in wealth or preferences in our model, we use investment flows into mutual funds and insurance companies. Our approach measures net inflows as a share of assets under management (AUM) for mutual funds, while for insurance companies we use the year-over-year quarterly changes in operating income, also as a share of AUM.¹⁴ This methodology builds on established approaches in the literature, following Darmouni et al. (2022) and van der Beck et al. (2022) for mutual fund flows and Kubitza (2023) for insurance company measures.¹⁵

¹⁴We employ year-over-year quarterly growth rates for insurers' operating income to account for the pronounced seasonality in this metric.

¹⁵Detailed data cleaning procedures are documented in Appendix C.2.

To extract the exogenous component of flows for each fund, we employ a two-stage orthogonalization procedure that first removes fund-level returns and then removes an equivalent of a value-weighted time fixed effects at the fund-category level.

First, we orthogonalize fund-level flows by contemporaneous returns for each investor group $g \in \{\text{Mutual Funds, Life Insurers, P\&C Insurers}\}$ and recover the “first-stage” residual $f_{it}^{g,FS,\perp}$ which represents a fund-level exogenous flow.

$$f_{it}^g = \beta^g \bar{R}_{it}^g + f_{it}^{g,FS,\perp} \quad (25)$$

Even though we have removed the fund-level returns, there still remains the potential concern that there are correlated flows across funds of similar types by informed investors. If these common flows correlated with firm issuance, it could create endogeneity problems. For instance, a surge in flows into investment-grade long-duration mutual funds might reflect market-wide expectations about future long-term investment opportunities and borrowing conditions. Thus, these flows could be correlated with factors driving firms’ fundamentals. To mitigate this concern, we define 6 investor categories as $c \in \{\text{IG/Long MFs, IG/Short MFs, HY/Long MFs, HY/Short MFs, Life Insurers, P\&C Insurers}\}$, where mutual funds are categorized based on what assets they hold.¹⁶ We then subtract the AUM-weighted average orthogonalized flows at the fund-category level:

$$f_{it}^\perp = f_{it}^{g,FS,\perp} - f_{ct}^\perp, \quad \text{where } f_{ct}^\perp = \frac{\sum_{i \in c} f_{it}^{g,FS,\perp} \cdot \text{AUM}_{i,t-1}}{\sum_{i \in c} \text{AUM}_{i,t-1}}. \quad (26)$$

By isolating each fund’s deviation from its category’s average flow, we obtain a measure that is more purely idiosyncratic and orthogonal to category-level fundamentals that might correlate with firm decisions. The category-level flow f_{ct}^\perp captures the investor-category time series variation critical to our measurement of demand-based risk, while the individual fund-level residual f_{it}^\perp provides our final measure of idiosyncratic investor demand shocks.

The next step is to aggregate our proxy of demand shocks to the bond type level as a share of its total market capitalization. To do this, we aggregate the residual flows in Equation (26) to the bond type-quarter level:

$$z_{nt}^{cs} = \sum_{i \in I_{nt}} \frac{\omega_{in,t-1} \text{AUM}_{i,t-1}}{\text{mktcap}_{n,t-1}} \times \hat{f}_{it}^\perp \quad (27)$$

¹⁶See Section 4.4 for detailed categorization of investor categories.

where I_{nt} is the set of funds that holds bond type n in period t , $\omega_{in,t-1}$ is the portfolio weight, $mktcap_{n,t-1}$ is the total market capitalization of all corporate bonds within bond type n , and \hat{f}_{it}^\perp is the orthogonalized net flows from Equation (26).¹⁷

4.1.3 Demand-based risk (dbr)

Next, we construct an empirical counterpart of the model’s asset-level demand-based risk parameter δ_t from equation (8). Our approach assumes a one-factor structure drives 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.

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 a principal component analysis.

Step 1: Construct Investor-Level Risk Matrix Ω . We begin by constructing an investor-level demand risk matrix Ω , which we assume remains constant over time. For each of the six investor categories (IG/Long MFs, IG/Short MFs, HY/Long MFs, HY/Short MFs, Life Insurers, P&C Insurers) c at time t , we calculate fund category-level orthogonal flows f_{ct}^\perp by taking the AUM-weighted averages of individual fund flows f_{it}^\perp within that category, as explained in equation 26. The matrix Ω is the $C \times C$ variance-covariance matrix of these category-level orthogonalized flows across time. Figure 6 shows the time series of f_{ct}^\perp . Life and P&C insurers have the lowest variance, while mutual funds that hold short securities have much more variance. We report the estimated Ω matrix in Table 5. Some of the 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. Importantly, in general, the off-diagonal terms are lower than the on-diagonal terms for each investor category, suggesting a firm can reduce its overall variance by diversifying its lenders across investor groups.

Step 2: Transform Ω to Asset-Level Risk. Having estimated the covariance matrix Ω of investor-category shocks, we now translate these into asset-level risk by weighting Ω with each bond type’s exposure to different investor categories. Let S_t be a $C \times N$ 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 . The asset-level variance-covariance matrix of demand risk is then constructed as $\Sigma_{it} = S'_{t-1}\Omega S_{t-1}$, which

¹⁷This 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).

is an $N \times N$ matrix.

Step 3: Principal Component Analysis to Compute Demand-Based Risk. 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 $S'_{t-1} \times f_t^\perp$, 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:

$$\underbrace{S'_{t-1}}_{N \times C} \times \underbrace{f_t^\perp}_{C \times T} = \alpha + \underbrace{\delta_{t-1}}_{N \times 1} \underbrace{F_t}_{1 \times T} + u \quad (28)$$

where F represents the first principal component capturing the dominant time-series factor, δ_{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 $\Sigma_{ut} = S'_{t-1} \Omega S_{t-1} = \delta_{t-1} \delta'_{t-1} + \Sigma_{ut}$, where δ_{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 B.1. 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 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 .

4.2 Investors' hedging needs affect prices

Having defined the key variables, we first test Hypothesis 1: whether idiosyncratic investor demand shocks affect equilibrium asset prices. We regress the relative credit spread measure cs_{fnt}^r on the exogenous flows into bond type n , z_{nt}^{cs} . We control for 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, to absorb characteristics that potentially impact firm issuance outside of prices.

$$cs_{f,t-1}^r(n) = \beta z_{t-1}^{cs}(n) + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} + \delta_4 DebtDue_{f,t-1} + \delta_5 \log(Assets)_{f,t-1} + \delta_6 dbr_{t-1}(n) + \alpha_t + \alpha_f + \epsilon_{fnt} \quad (29)$$

We present the results in columns (1) and (2), Panel A of Table 6. In line with hypothesis (1), we find that positive exogenous net inflows to a given bond type n reduce that 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 (1): holding all else constant, a 1 standard deviation decrease in a given bond type's exogenous net flows leads to a 0.004 percentage point increase in a firm's relative credit spread of that bond type. This translates into a 0.01 p.p. increase in credit spreads.¹⁸

4.3 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. We 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_{nt}^{cs}) 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 and market-wide movements (see Equation 26). If, for example, certain investors have knowledge that BBB-rated firms would face difficulties issuing long-duration debt

¹⁸The standard deviation of the independent variable is 0.079 from Table 4, times the coefficient in Column (1) of Table 6 equals 0.004. We multiply this by the average $cs_{t,-f}$ in the data of 2.1% and get 0.01%.

and thus cause 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. Our identification hypothesis is that the remaining variation in the instrument reflects exogenous shocks to household wealth and insurer operating profits that are very unlikely to be correlated with unobservable fundamentals that affect firm decisions to issue certain bond types.

Equipped with an instrument for the relative credit spread cs_{fnt}^r , we can test Hypothesis 2 by running the following second-stage instrumental variable (IV) regression:

$$issuance_{ft}(n) = \gamma_1 cs_{f,t-1}^r(n) + \gamma_2 dbr_{t-1}(n) + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} + \delta_4 DebtDue_{f,t-1} + \delta_5 \log(Assets)_{f,t-1} + \alpha_t + \alpha_f + \nu_{fnt} \quad (30)$$

where $issuance_{ft}(n)$ is the *net* issuance of by f , of bond-type n , at quarter t as a percentage of total assets of the firm in the previous period, i.e., $issuance_{ft}(n) = \frac{amt_{fnt} - amt_{fn,t-1}}{assets_{f,t-1}} \times 100$.¹⁹ Our main dependent variable in this section is the lagged \hat{cs}_{fn}^r . In the next section we discuss dbr . We lag these variables further avoid econometric issues of bad controls.

Our preferred specification, which includes controls, firm and time fixed-effects, is reported in columns (5) of Panel (A) in Table 6. 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. Our results remain qualitatively similar and statistically significant once we add firm-month fixed effects in Column (6) to control for unobservable, time-varying firm fundamentals that could affect issuance (similar to Khwaja and Mian (2008)). However, our preferred specification is Column (5), which exploits the extensive margin of issuance and thus is not affected by the fact that not all firms issue multiple bond types simultaneously. 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 0.3 percentage point increase in the firm's issuance to assets ratio for that bond type in that month.²⁰ This is economically significant and represents 18% of

¹⁹Note 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 also restrict our sample to bond-types a firm f has outstanding in the previous year. Since this variable is defined at the firm-bond type-quarter level, 93% of its values are zero, which simply reflects that most firms rarely issue every bond type in a given quarter.

²⁰From Table 4, one standard deviation of the relative credit spread cs_{fnt}^r is 0.16, the coefficient estimate is 2.085, so $2.085 \times 0.16 = 0.33$.

median conditional quarterly issuance of a bond type n (about \$156 million). We show the OLS results in Table E.1 for comparison, which are near zero, though still slightly negative. This is consistent with an attenuating bias, potentially arising from unobserved firm demand for a given bond type coinciding with higher credit spreads.²¹

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 actively cater to investor demand shocks for certain kinds of assets by supplying them.

4.4 Demand-based risk affects bond supply

In this subsection, we test whether asset-level demand-based risk impacts firm issuance decisions. Specifically, 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. Hence, we construct the instrument for dbr as

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

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 $z_{cnt}^{cs} = \sum_{i \in I_{cnt}} \frac{\text{param}_{in,t-1}}{\text{amtout}_{n,t-1}} \times f_{it}^{SS,\perp}$.

Panel A of Table 6 shows that the instrument is relevant for demand-based risk. An increase in z_{nt}^{dbr} causes an increase dbr_{nt} . Intuitively, z_{nt}^{dbr} maps to the variance of the demand shock $S_{i,t-1} f_t^\perp$, and higher variance maps to a larger loading on the common demand factor, making the instrument relevant. 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

²¹For 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.

credit spreads and dbr , using the same regression in equation (30).

Columns (3) and (4) of Table 6 show the IV results instrumenting only dbr_{nt} , and columns (5) and (6) show the results instrumenting both cs_{fnt}^r 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 and minimize their exposure to unreliable suppliers, firms will also diversify their suppliers of credit in corporate bond markets and value issuing bonds for which supply is less risky. Our results survive controlling for unobservable time-varying firm fundamentals via adding firm-month fixed effects, though our preferred specification is Column (5), where we include variation within firm across time. 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 0.03 percentage point increase in the firm's issuance to assets ratio for that bond type in that month (about \$14 million).²² This is economically significant and represents about 2% of median quarterly conditional net issuance of a bond type n .

There is significant heterogeneity across firms in their responsiveness to relative credit spreads and dbr when selecting bonds to issue. Figure 9 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 10 shows that investment grade firms tend to be more sophisticated than high-yield firms, with A-rated firms more responsive to credit spreads while BBB-rated firms are slightly more responsive to dbr .

To support our main results, we conduct a range of robustness tests. A recent paper Haddad et al. (2025) presents ways to validate instruments for causal inferences in asset pricing. While the goal of our paper is to show how firms respond to plausibly exogenous variation in prices, not to estimate investor demand elasticities, the test they propose to ensure the instrument is uncorrelated with bond characteristics is useful. We run a similar test using the mutual fund version of our instrument in Internet Appendix E.2, and find that treated bonds (those held by funds with higher flows) are not statistically different from control bonds (those held by funds with lower net flows) in ex-ante credit spreads or duration.

As further robustness, in Internet Appendix E.3, we show our main results are robust to recomputing the instruments z^{cs} and z^{dbr} using only flows in mutual funds or only flows in insurance companies. Furthermore, we leverage the idea that retail flow-induced trading is more likely to be

²²One standard deviation of the dbr_{nt} is 0.052, the coefficient estimate is 0.593, so $0.593 \times 0.052 = 0.031$.

uninformed, relaxing the exclusion restrictions of our instrument. Results are robust to constructing the instruments using only flows from retail funds (see Internet Appendix E.4. This gives us confidence that our instrument satisfies the exclusion restriction. We further strengthen our results by leveraging variation in 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) in Internet Appendix E.5, and find similar firm issuance responses.

Finally, in Internet Appendix E, we also examine how different dimensions of bond types drive firm issuance decisions. We augment our baseline IV specification by interacting each bond type dimension with time fixed effects. This approach tests whether firms' issuance decisions respond to variation in prices and demand-based risk within the remaining dimensions after controlling for one particular dimension. Our identification would be problematic if firms only responded along a single dimension such as time-to-maturity or issue size, as this would closely replicate existing findings in the literature. Instead, we demonstrate that our results are robust across specifications, with firms responding to price and demand-based risk variation within all five dimensions we examine.

4.5 Demand-based risk and the Cross-section of Bond Returns

We now move on to our last hypothesis, in which we test the correlation between *dbr* and returns. The model predicts that higher demand-based risk correlates with lower expected returns in the cross section, which means higher prices (lower credit spreads). We show in Table 7 (Table F.1) that *dbr* and excess returns (relative credit spreads) 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 financial fragility.

5 Inspecting the mechanism

This section examines the economic mechanisms underlying our main findings by testing three key predictions of our theoretical framework. First, we show that firms with lower demand-based risk exhibit greater resilience to systematic credit shocks, as measured by their CDS beta relative to

market indices. Second, we demonstrate that sophisticated financing decisions create shareholder value: firms issuing bonds with favorable relative credit spreads generate positive abnormal returns, while those reducing demand-based risk experience improved credit conditions. Third, we provide evidence for asset scarcity by showing that investors with larger existing holdings disproportionately absorb new issuance of the same bond type, and that firms face greater difficulty attracting new lenders during periods of distress. Together, these results support our central thesis that diversifying across investor types enhances firm resilience and creates economic value.

5.1 Low demand-based risk increases resilience

The micro-foundations for why firms care about financial fragility stem from their understanding that access to a diverse set of institutional investors allows them to better maintain capital access during periods of distress and navigate market turmoil more effectively. We provide evidence for this mechanism by showing that a firm’s exposure to demand-based risk affects its resilience.

Our proxy for resilience is the firm exposure to aggregate market risk, which we measure using the beta of a firm’s CDS spreads relative to the CDX index.²³ We then test how variation in firm-level dbr correlates to variation in 5-year forward CDS β . The higher a firm’s β , the lower the resilience. We regress estimated betas on firm level demand-based risk:

$$\beta_{f,t \rightarrow t+s}^{CDS} = \gamma dbr_{f,t} + \delta X_{f,t} + \alpha_t + \alpha_f + \varepsilon_{f,t}, \quad (32)$$

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 8 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.

²³Specifically, we begin at the subsidiary level and compute the issuer-level CDS using the covariance of the issuer CDS and CDX index, where CDS is calculated from U.S. daily data. Next, we aggregate to firm-month level CDS betas, weighting by the amount outstanding of each subsidiary’s.

While β focuses on the systematic undiversifiable component of firms' risk, the same mechanism should also push firms to reduce their idiosyncratic risk. We corroborate this hypothesis by showing evidence that less diversified firms exhibit greater bond-return volatility. Figure 11 shows 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. Thus, firms with lower dbr are reducing their overall exposure to investor-demand driven risk.

5.2 Firm sophistication creates value

Firms that are able to issue bonds in high demand or low risk should create value by doing so. We can test this directly by running an event study analysis around issuance announcement of a bond type associated with a relative credit spread and/or low demand based risk. To do this, we construct two dummy variables: (1) $LowCS_{ft}$, which takes the value of 1 if the firm issues any bond type in time t that has a lower credit spread relative to its long term average, i.e., $cs_{ft}^r < 0$ and zero otherwise; (2) $LowDBR_{ft}$, which takes the value of 1 if the firm issues any bond type in time t with lower dbr than the average dbr of bonds that the firm has outstanding in the previous period and zero otherwise. That is, by adding the newly issued bond to its portfolio, the firm lowers its resulting dbr . We then regress the 2-day returns in excess of the market on an indicator variable $SophisticatedIssuance_{ft}$ that represents either of these two dummy variables:

$$r_{ft}^e = \beta_0 + \beta_1 SophisticatedIssuance_{ft} + \beta_2 IssuanceSize_{ft} + \beta_3 AvgCDS_{f,t-1} + \beta_4 TobinsQ_{f,t-1} + \alpha_f + \epsilon_{ft}, \quad (33)$$

where we use three dependent variables: (1) the abnormal stock return, defined as the firm's stock return from the day before issuance to the day after issuance minus the market return, (2) enterprise value²⁴ returns, computed as the weighted sum of bond and equity excess returns over the same two-day issuance window, with weights equal to their shares of total enterprise value, and (3) the change in CDS spreads, measured as the firm's CDS spread change relative to the CDX index over the same two-day issuance window.²⁵ We control for firm-level for previous period average CDS,

²⁴We calculate enterprise value as the sum of a firm's market capitalization and total debt outstanding.

²⁵Ideally, we would use bond values rather than CDS spreads for this exercise. However, because not all bonds trade frequently, we would not be able to conduct this high-frequency analysis for a comprehensive sample of firms.

Tobin's Q, and issuance size normalized by prior period assets.

We report results in the first two columns of Table 9, where Panel (a) reports results issuing bonds with low relative credit spreads and Panel (b) reports results for bonds with low *dbr*. Column (2) of Panel (a) shows that 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 represents 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 9 using the firm's overall enterprise value also shows a positive effect; thus the value-add is not simply a transfer from existing debt to equity holders.

We find further that this behavior does not significantly increase the firm's default risk.²⁶ Column (4) of Table 9, Panel (a), presents the results for issuance-driven changes in the firm's CDS relative to the CDX index. 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*.

5.3 Evidence of asset scarcity

Central to the mechanism we highlight in this paper is that other agents in the economy, such as financial intermediaries, cannot supply the specific assets that investors demand. We provide evidence for this asset scarcity and the special role of non-financial firms by showing that when a firm issues additional bonds of type n , investors with larger pre-issuance holdings of type n absorb a disproportionately larger share of the new supply. The idea is that although we do not directly observe hedging demand, we proxy this demand using portfolio weights for each bond type n . To show this, we use the eMAXX data, which has the advantage of including not only insurers and mutual funds but other bond holders as well, including some pension funds and hedge funds.

Therefore, we rely on CDS, which are more liquid, to proxy for the value of firms' debt.

²⁶Note $\Delta CDS_{f,t} = CDS_{f,t+1} - CDS_{f,t-1}$ 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.

Specifically, we use bond type-by-quarter data and, conditional on positive net issuance in that bond type, regress changes in portfolio weights of a given bond type on issuance in that bond type, interacted with the investor’s previous portfolio weight in that bond type:

$$\Delta\omega_{it}(n) = \beta_1 \text{issuance}_t(n) \times \omega_{i,t-1}(n) + \beta_2 \text{issuance}_t(n) + \beta_3 \omega_{i,t-1}(n) + \alpha_{it} + \epsilon_{int}, \quad (34)$$

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 , and $\text{issuance}_t(n) = \frac{\text{amt}_t(n) - \text{amt}_{t-1}(n)}{\text{amt}_{t-1}(n)}$ 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.

The positive β_1 coefficient reported in Table 10 shows that investors with higher initial exposure to a bond type purchase 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. These results are at odds to a pure diversification motive, which would imply $\beta_3 < 0$; 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.

5.4 Fewer new lenders in bad times

Finally, why do firms care about maintaining low demand-based risk? If firms could costlessly rebalance their capital structure at any time, they would not need to maintain low demand-based risk continuously and could simply issue bonds unaffected by demand shocks when such shocks occur. Firms would thus value diversifying across investors only if it is costly to borrow from new investors when they need capital. Under this constraint, by borrowing from many investors during favorable periods, firms can diversify across idiosyncratic investor shocks and maintain credit access when facing negative shocks. Theoretically, given information asymmetries between firms and investors, investors learn from market prices. When corporate bond prices are low, investors cannot fully determine whether this reflects deteriorating fundamentals or liquidity shocks affecting intermediaries. Consequently, intermediaries are more likely to purchase bonds from firms already

within their investment universe, particularly during 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. Again we use the eMAXX data for this exercise. 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.

$$NewInvestors_{ft} = \beta_1 avgCDS_{ft} + \beta_2 CDX_t + \beta_3 TobinsQ_{f,t-1} + \beta_4 IssuanceSize_{ft} + \alpha_t + \alpha_f + \epsilon_{ft} \quad (35)$$

Table 11 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 financial fragility.

In summary, firms benefit from the diversification across investors. Because investor demand is both idiosyncratic and insatiable, firms whose debt is concentrated among a few investors have 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.

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 demand-based risk. Our findings highlight the important role for firms in financial markets: by tailoring securities to match heterogeneous investor preferences, firms effectively select their investor base while managing their exposure to investor-specific demand shocks.

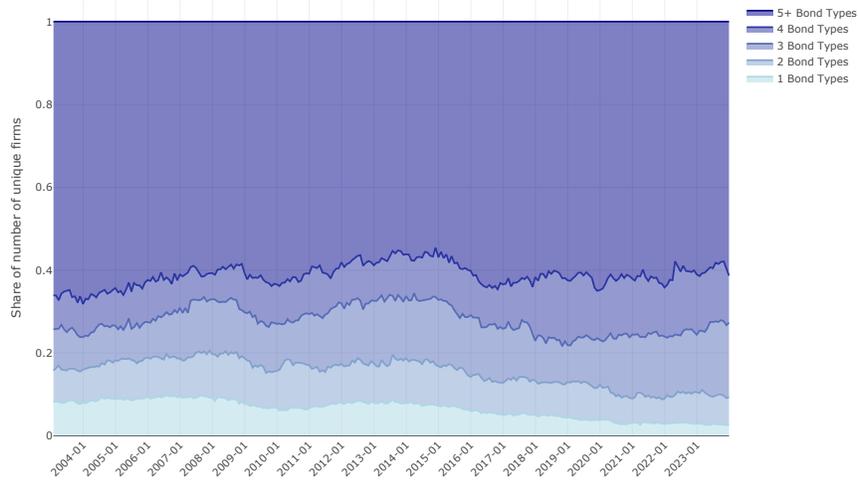
We support this interpretation with a theoretical framework in which risk-averse investors, facing short-selling constraints and incomplete hedging opportunities, benefit from firms supplying bonds backed by varied cash flows. Firms, in turn, optimize their capital structure by weighing the benefits

of maximizing issuance proceeds against the importance of reducing their financial fragility, which importantly comes in part from investors' demand shocks. 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. These actions are especially pronounced among larger and high-rated firms. Importantly, such strategic behavior is value-enhancing for firms: issuing more expensive bond types boosts firm equity value, while issuing bonds with lower demand-based risk reduces firm CDS.

Our results challenge the traditional Modigliani-Miller perspective by highlighting that firms integrate investor preferences and diversification considerations into their optimal capital structure decisions. Firms effectively resemble financial intermediaries by strategically engineering securities that fit investor demands. They are also forward-looking in designing a bond capital structure that ensures sustained market access. As credit markets increasingly move away from traditional banks, it is crucial to better understand the way firms interact with bond markets. Our paper contributes to this understanding and presents several promising avenues for further research.

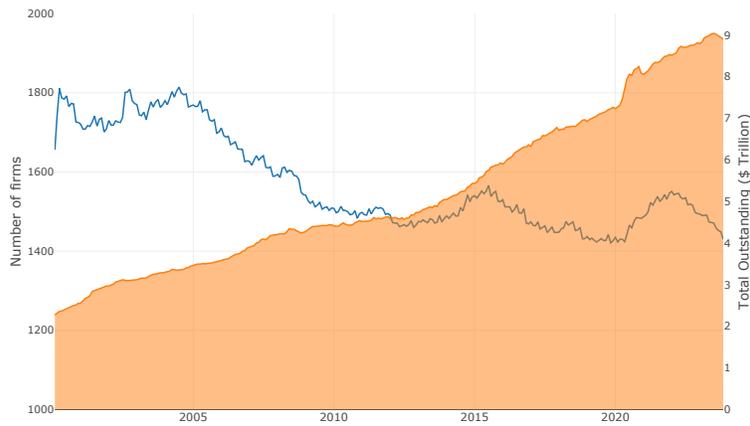
These insights have broad implications for understanding corporate bond market dynamics. Specifically, firms frequently issuing multiple distinct bonds to accommodate investor demands may contribute to persistent illiquidity in corporate debt markets (Bao et al. (2011); Goldstein and Hotchkiss (2020)). Exploring the welfare implications of this market segmentation and the broader application of diversification motives to other sources of corporate finance represent important additional directions for further research.

Figure 2: One firm can issue many bond types



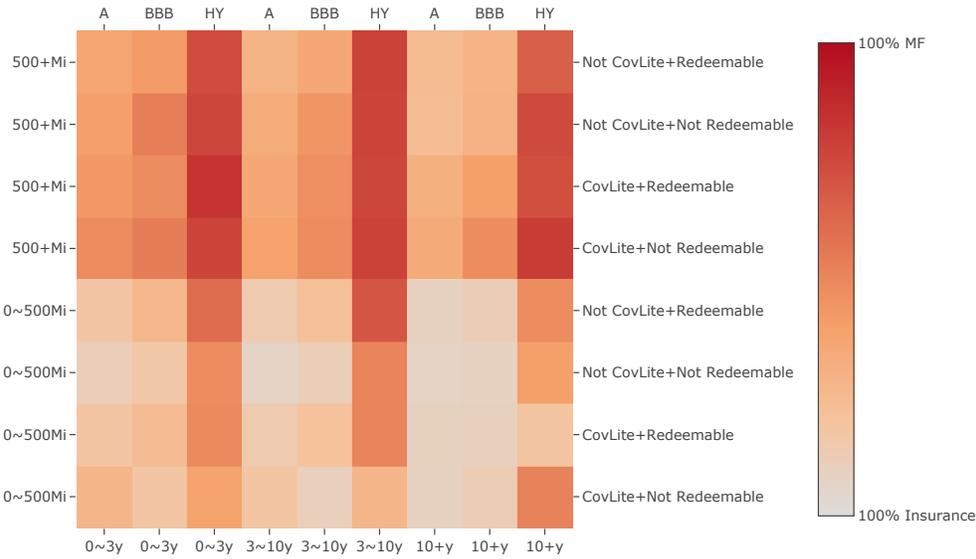
Note: This figure shows the distribution of bonds outstanding by the number of bond types the issuer has outstanding, from January 2003 to December 2023. Bond type is defined by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption.

Figure 1: Bond issuers and corporate bonds outstanding



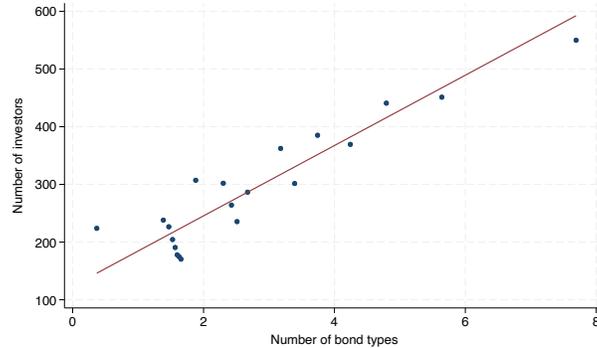
Note: This figure shows the number of U.S. firms with outstanding bonds (line) and the total amount of outstanding corporate bonds over time (area), from January 2000 to October 2023.

Figure 3: Mutual funds holdings vs. insurer holdings



Note: This figure shows, for each bond type, the average share of outstanding issuance held by mutual funds relative to that held by insurance companies. Bond type is defined by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. For each cell, the share is calculated as the amount outstanding held by mutual funds divided by the total amount outstanding in that bond type. Data is quarterly from 2003 Q1 to 2023 Q4.

Figure 4: Relationship between bond type variety and investor heterogeneity



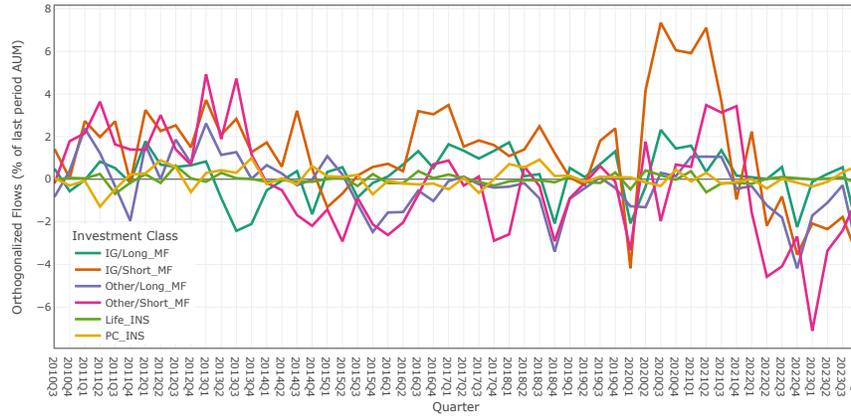
Note: This figure presents the relationship between the diversity of bond types a firm issues and the heterogeneity of its investor base. The y-axis is the number of investors within a firm, while the x-axis is the number of bond types a firm issues. We control for firm's total amount of bonds outstanding and year fixed effects. Data is quarterly from 2003 Q1 to 2023 Q4. All variables are winsorized at the 1st and 99th percentiles.

Figure 5: Long-short portfolio returns



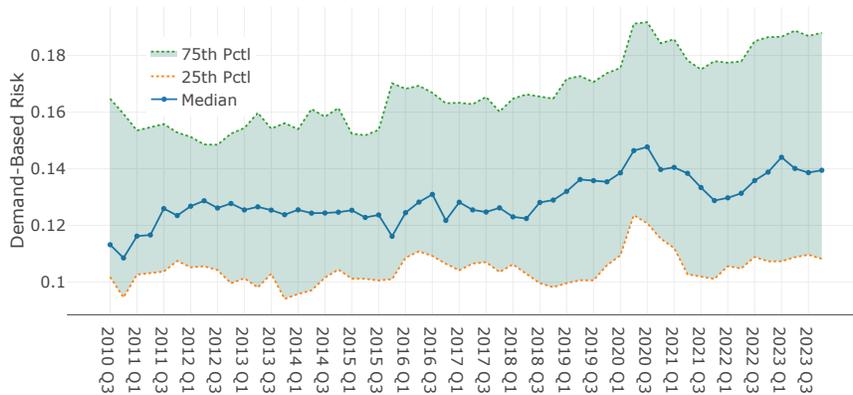
Note: This plot shows the cumulative return for two triple sorted long-short portfolios. The first long-short portfolio is long bonds that are held in high shares by insurers and short bonds that are held in low shares by insurers, within rating and maturity bucket. The second long-short portfolio long 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 6: Time-series of average orthogonalized flows for each investor category, as % of AUM



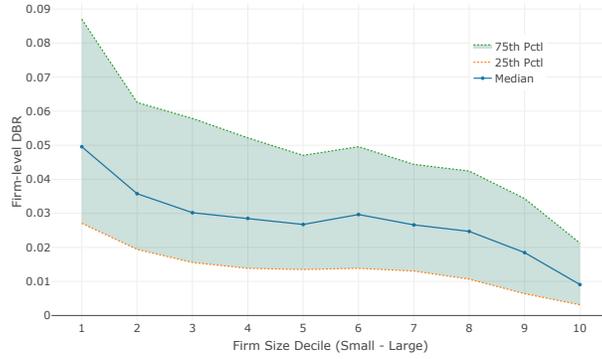
Note: This figure shows the time-series of orthogonalized flows for each of the six investor category from 2010 Q3 to 2023 Q4. For each investor category c in quarter t , orthogonalized flows are computed as $f_{ct}^\perp = \frac{\sum_{i \in c} f_{it}^{FS,\perp} \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$, as explained in Equation (26). Data source: FISD, CRSP for mutual funds, NAIC for insurers.

Figure 7: Time-series of demand-based risk

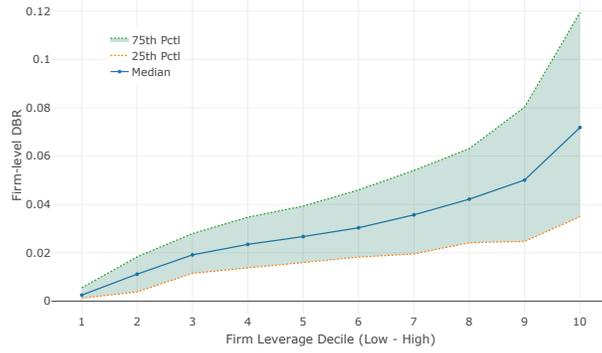


Note: This figure shows the time series of demand-based risk from 2010 Q3 to 2023 Q4. Demand-based risk is constructed as described in Section 4.4. The blue dotted line represents the median demand-based risk, weighted by amount outstanding, while the green shaded area shows the corresponding weighted interquartile range.

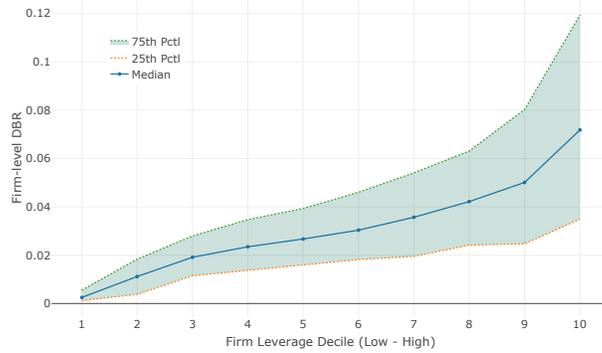
Figure 8: Cross-sectional firm-level demand-based risk



(a) By size deciles



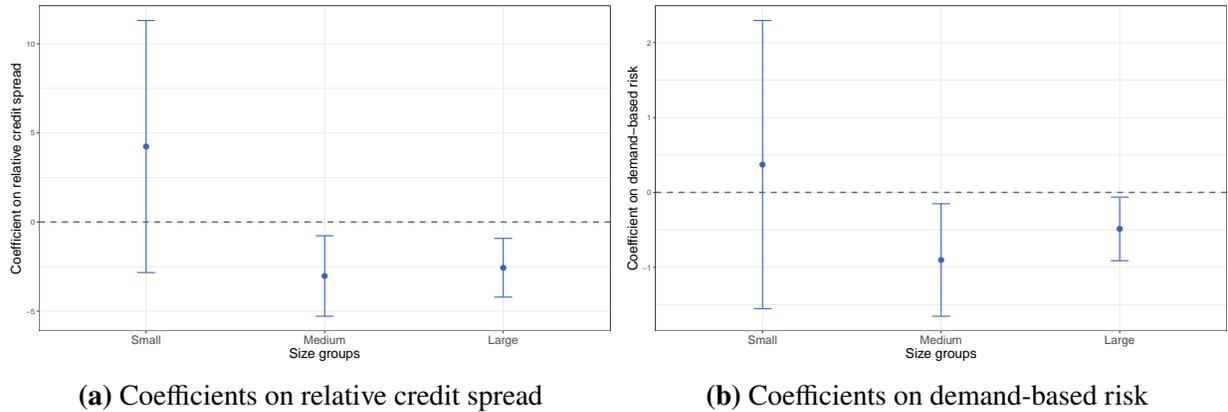
(b) By leverage deciles



(c) Panel (b): By leverage deciles

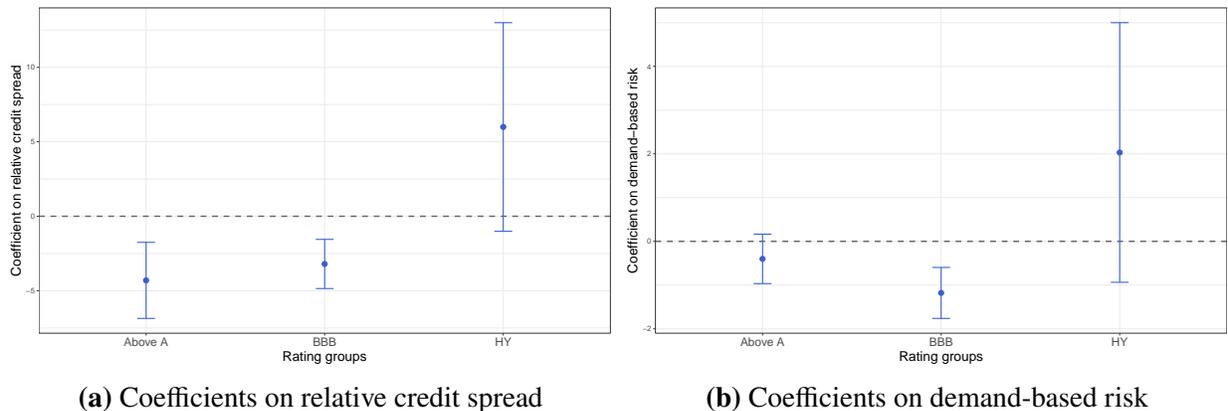
Note: This figure shows the cross-sectional median and interquartile range of firm-level demand-based risk. Panel (a) groups firms by size decile, Panel (b) by leverage decile, and Panel (c) by maximum credit rating. Firm-level demand-based risk is computed as $dbr_{ft} = \sum_{n \in f} \frac{amt_{out_{fnt}}}{ATQ_{ft}}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

Figure 9: IV heterogeneous effects by firm size



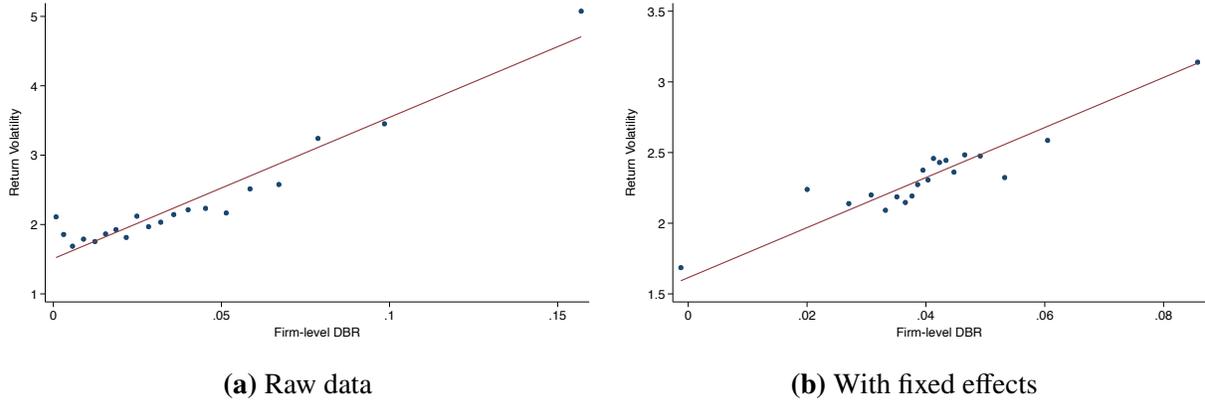
Note: This figure shows the IV heterogeneous effects, subsampling by firms' size in the prior period. We control for firm characteristics including Tobin's Q, leverage, average CDS, debt coming due, and log assets in the previous period. Firm fixed effect and month fixed effect are included. Data is quarterly from 2010 Q3 to 2023 Q4. Standard errors are clustered at the firm level.

Figure 10: IV heterogeneous effects: subsample by firm credit rating



Note: This figure shows the IV heterogeneous effects, subsampling by firms' maximum credit rating in the prior period. 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. Standard errors are clustered at the firm level.

Figure 11: Firm demand-based risk and bond portfolio return volatility



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 as $dbr_{ft} = \sum_{n \in f} \frac{amt_{out_{fnt}}}{ATQ_{ft}} \times dbr_{nt}$. The y-axis is the firm-year level bond portfolio volatility, defined as: $vol(ret)_{fy} = StdDev(\sum_{b \in f} w_{bf,t-1} r_{bt})_{fy}$, where $w_{bft} = \frac{amt_{bft}}{amt_{ft}}$ is portfolio weight at the firm-bond-month level, and r_{bt} denotes monthly bond returns. Data is yearly from 2010 to 2023. Firms with fewer than 3 months of valid bond returns per year are excluded. Figure (a) shows the binscatter for raw data; and Figure (b) includes firm and year fixed effects. Return volatility, firm-level demand-based risk, Tobin's Q, leverage, and debt coming due are winsorized at the 1st and 99th percentiles.

Table 1: Summary statistics of investor categories**Panel (a): Inventory 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

Panel (b): Average fund and bond characteristics by investor category

Investor category	Avg # funds	Avg AUM	Avg flows%	Avg returns	Avg orth flows%	Avg holdings share	Avg maturity	Avg yield
All Investors	855.33	811.25	0.20	2.67	0.11	0.12	8.87	4.41
IG/Long MFs	1,141.29	951.45	0.61	0.79	0.27	0.07	9.75	4.46
IG/Short MFs	314.36	751.89	1.53	0.43	1.67	0.04	5.05	3.63
Other/Long MFs	894.92	701.00	-0.13	1.06	-0.26	0.09	9.82	4.58
Other/Short MFs	164.24	415.16	0.54	1.65	-0.11	0.02	5.54	5.18
P&C Insurers	1,652.81	282.29	0.02	2.88	0.03	0.05	9.52	4.39
Life Insurers	964.36	1,741.04	0.01	4.58	-0.02	0.29	9.93	4.47

Panel (c): Average portfolio weight by investor category

	Rating			Remaining Maturity			Size		Covlite		Redemption	
	A	BBB	HY	< 3 years	3 to 10 years	≥ 10 years	< 500 million	≥ 500 million	True	False	Yes	No
All Investors	40.08	37.49	22.43	15.46	56.72	27.82	34.76	65.24	24.33	75.67	82.50	17.50
IG/Long MFs	46.92	41.84	11.24	18.20	53.87	27.93	20.20	79.80	27.90	72.10	77.07	22.93
IG/Short MFs	56.19	39.27	4.54	56.13	43.10	0.77	21.24	78.76	35.80	64.20	66.07	33.93
Other/Long MFs	4.79	13.62	81.59	9.11	78.41	12.48	33.10	66.90	22.11	77.89	91.91	8.09
Other/Short MFs	1.87	7.27	90.86	19.20	79.12	1.68	32.88	67.12	19.27	80.73	93.71	6.29
PC Insurers	54.97	35.41	9.62	22.87	66.43	10.70	32.95	67.05	26.34	73.66	79.32	20.68
Life Insurers	47.42	44.30	8.28	12.20	48.75	39.05	42.56	57.44	22.42	77.58	82.76	17.24

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.

Table 2: Bond type description

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, +∞)	Bonds with a remaining maturity of more than 10 years
Size	[0m, 500m)	Bonds with an outstanding amount of less than 500 million
	[500m, +∞)	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

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 merge underpopulated bond types to ensure each type contains at least 50 bonds per quarter over 2003 Q1 - 2023 Q4. Specifically, we consolidate the original 72 combinations into 60 groups by merging: (1) 4 bond types that are HY, over 10 year ttm, over 500mm outstanding amount into one; (2) 4 bond types with HY-rated, 0-3 year ttm, over 500mm outstanding amount into one; (3) 4 bond types with BBB-rated, over 10 year ttm, over 500mm outstanding amount into one; (4) 2 bond types with HY-rated, 3-10 year ttm, over 500mm outstanding amount, with redemption option into one; (5) 2 bond types with A-rated, over 10 year time-to-maturity, over 500mm outstanding amount, with redemption option into one; and (6) 2 bond types with BBB-rated, 3-10 year ttm, over 500mm outstanding amount, with redemption option into one.

Table 3: Summary statistics of firms by number of bond types

	Firms with 1 Bond Type			Firms with multiple Bond Types			Full sample		
# Firms	1341			819			2160		
% A	4.08%			20.88%			15.8%		
% BBB	13.3%			43.23%			34.18%		
% HY	82.61%			35.89%			50.02%		
Bond Characteristics									
	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev
Credit Spread	5.74	5.15	3.35	2.15	1.6	1.97	2.27	1.64	2.13
Time-to-Maturity	5.87	5.58	3.29	11.08	7.25	10.42	10.91	7.17	10.31
Duration	4.34	4.19	1.87	7.02	5.85	4.54	6.93	5.73	4.51
Bond Outstanding (M)	297.89	249.98	231.71	527.14	400	529.87	519.76	400	524.49
Market Cap (M)	295.54	236.1	236.75	551.53	403.99	557.52	543.29	397.56	551.97
Firm Characteristics									
	Mean	Median	Stdev	Mean	Median	Stdev	Mean	Median	Stdev
Assets (B)	3.3	1.46	9.65	24.49	8.75	45.46	21.04	6.78	42.5
Market Cap of Equity (B)	2.51	0.96	6.57	25.07	7.1	82.51	21.65	5.27	76.48
Enterprise Value (B)	2.84	1.28	6.66	28.57	8.8	86.34	24.68	6.65	80.11
Number of Investors	67.63	55	56.41	326.8	212	343.82	284.6	165	329.61
Age 16.16	18.03	18.08	16	12.46	31.2	30	15.93	29.06	27
Leverage	0.4	0.41	0.19	0.34	0.33	0.16	0.35	0.34	0.17
Profitability	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Bonds/Debt	0.58	0.54	0.31	0.57	0.58	0.29	0.57	0.58	0.29
Bonds/Asset	0.22	0.19	0.16	0.18	0.17	0.12	0.19	0.17	0.13
Demand-Based Risk	0.04	0.04	0.03	0.03	0.03	0.03	0.04	0.03	0.03
Mutual Funds	0.26	0.25	0.17	0.15	0.11	0.13	0.17	0.12	0.14
Insurers	0.14	0.06	0.19	0.35	0.34	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

1 *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. 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.

Table 4: Descriptive statistics of key variables

Panel A: Unconditional full sample						
Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
$issuance_{ft}(n)$	133,066	0.072	0.540	0.000	0.000	0.000
$cs_{f,t-1}^r(n)$	133,066	0.004	0.160	-0.051	0.003	0.058
$cs_{f,t-1}(n)$	133,066	1.916	1.468	0.867	1.523	2.516
$z_{t-1}^{cs}(n)$	133,066	0.044	0.079	0.0004	0.039	0.086
$dbr_{t-1}(n)$	133,066	0.119	0.052	0.080	0.109	0.153
$z_{t-1}^{dbr}(n)$	133,066	0.021	0.035	0.002	0.007	0.024
$dbr_{f,t-1}$	132,927	0.032	0.030	0.016	0.027	0.041
Tobin's $Q_{f,t-1}$	133,066	0.042	0.066	0.015	0.024	0.041
Leverage $_{f,t-1}$	133,066	0.336	0.146	0.236	0.336	0.436
Average CDS $_{f,t-1}$	133,066	0.014	0.013	0.006	0.009	0.015
Debt coming due $_{f,t-1}$	133,066	0.006	0.011	0.000	0.000	0.007
$\text{Log}(\text{assets})_{f,t-1}$	133,066	10.412	1.258	9.574	10.396	11.195
β^{CDS}	53,526	0.460	0.608	0.068	0.301	0.626
Panel B: Conditional on positive issuance						
$issuance_{ft}(n)$	5,447	2.167	1.468	0.829	1.848	4.069
$cs_{f,t-1}^r(n)$	5,447	0.002	0.119	-0.050	0.004	0.051
$cs_{f,t-1}(n)$	5,447	2.002	1.370	1.079	1.624	2.489
$z_{t-1}^{cs}(n)$	5,447	0.055	0.086	0.005	0.050	0.102
$dbr_{t-1}(n)$	5,447	0.120	0.051	0.085	0.106	0.146
$z_{t-1}^{dbr}(n)$	5,447	0.022	0.035	0.002	0.008	0.025
$dbr_{f,t-1}$	5,445	0.033	0.029	0.016	0.026	0.041
Tobin's $Q_{f,t-1}$	5,447	0.045	0.071	0.016	0.024	0.044
Leverage $_{f,t-1}$	5,447	0.343	0.147	0.245	0.350	0.435
Average CDS $_{f,t-1}$	5,447	0.012	0.012	0.005	0.008	0.013
Debt coming due $_{f,t-1}$	5,447	0.008	0.012	0.000	0.00000	0.011
$\text{Log}(\text{assets})_{f,t-1}$	5,447	10.581	1.245	9.707	10.561	11.424
β^{CDS}	2,448	0.438	0.569	0.067	0.278	0.595

Note: This table shows the descriptive statistics for key variables. Panel A shows the summary statistics across full sample of Table 6, 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. $\beta_{f,t \rightarrow t+s}^{CDS}$ is a time-varying measure of firm's resilience from 2010 Q3 to 2018 Q4. 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 $issuance_{fnt}$, $cs_{f,t-1}^r$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles.

Table 5: 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* measure. We use the full time series of orthogonalized flows from 2010 Q3 to 2023 Q4 to calculate the covariance matrix of $f_{ct}^\perp = \frac{\sum_{i \in c} f_{it}^\perp \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$. 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 than 10 years is 95% or more across time; otherwise, they are considered as Long funds. Data source: WRDS bond return, NAIC, and CRSP.

Table 6: How relative credit spreads and demand-based risks affect firms net issuance

Panel A: First stage test for flow-based instruments						
	$cs_{f,t-1}^r(n)$		$dbr_{t-1}(n)$		$cs_{f,t-1}^r(n)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z_{t-1}^{cs}(n)$: Exogenous net flows	-0.056*** (0.006)	-0.071*** (0.007)			-0.048*** (0.007)	-0.053*** (0.008)
$z_{t-1}^{dbr}(n)$			0.475*** (0.004)	0.559*** (0.004)	-0.050*** (0.014)	-0.107*** (0.016)
Tobin's $Q_{f,t-1}$	0.001 (0.011)		0.012*** (0.003)		0.001 (0.011)	
Leverage $_{f,t-1}$	0.002 (0.008)		0.014*** (0.002)		0.002 (0.008)	
Debt coming due $_{f,t-1}$	-0.035 (0.044)		0.022* (0.012)		-0.037 (0.044)	
Average CDS $_{f,t-1}$	-0.062 (0.063)		0.128*** (0.017)		-0.057 (0.063)	
Log assets $_{f,t-1}$	-0.002 (0.002)		0.004*** (0.0005)		-0.002 (0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{ft}(n)$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r(n)$: Relative credit spread	-1.483*** (0.544)	-1.113** (0.454)			-2.085*** (0.695)	-1.970*** (0.687)
$dbr_{t-1}(n)$: Demand-based risk			-0.226* (0.123)	-0.266** (0.112)	-0.593*** (0.189)	-0.773*** (0.218)
Tobin's $Q_{f,t-1}$	0.071 (0.051)		0.074* (0.043)		0.079 (0.058)	
Leverage $_{f,t-1}$	-0.189*** (0.045)		-0.186*** (0.044)		-0.176*** (0.046)	
Debt coming due $_{f,t-1}$	1.515*** (0.266)		1.572*** (0.249)		1.497*** (0.280)	
Average CDS $_{f,t-1}$	-0.759** (0.320)		-0.628** (0.264)		-0.693* (0.378)	
Log assets $_{f,t-1}$	-0.072*** (0.010)		-0.069*** (0.011)		-0.071*** (0.011)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	8.86	59.24	290.52	2509.96	39.21	32.32
Observations	133,066	133,066	133,066	133,066	133,066	133,066
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-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 $t - 3$. 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 as described in Equation 24 and Section 4.4. $issuance_{ft}(n)$, $cs_{f,t-1}^r(n)$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level.

Table 7: Relationship between demand-based risk and excess return

	$return_t^e(n)$: Excess return				
	Panel regression				Fama-MacBeth
	(1)	(2)	(3)	(4)	(5)
$dbr_t(n)$	-0.0432* (0.0236)	-0.0426 (0.0315)	-0.0514** (0.0230)	-0.0477** (0.0227)	-0.0568*** (0.0203)
$Duration_{t-1}(n)$			0.0170 (0.0626)	0.0568 (0.0617)	0.0256 (0.0635)
$Average\ CDS_{t-1}(n)$			0.143*** (0.0486)	0.0537 (0.0392)	0.144*** (0.0487)
Month FE		✓	✓		
Rating \times Month FE				✓	
Observations	9,340	9,340	9,340	9,340	9,340
R-squared	0.000	0.667	0.671	0.740	0.476

Note: This table shows the regression results of excess bond returns on demand-based risk using bondtype-month level data from July 2010 to December 2023. The dependent variable $ret_t^e(n)$ is computed as monthly bond returns minus the 30-day Treasury bill rate, and weighted by amount outstanding. 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. All independent variables are standardized (z-scored). The dependent variable is winsorized at the 1st and 99th percentiles. Standard errors are clustered at the time level.

Table 8: Impact of firm's demand-based risk on credit betas

	$\beta_{f,t \rightarrow t+s}^{CDS}$			
	(1)	(2)	(3)	(4)
dbr_{ft}	1.773*** (0.294)	1.292*** (0.378)	4.631*** (0.379)	1.317*** (0.447)
Tobin's Q_{ft}			-0.0003 (0.001)	0.0002 (0.001)
Leverage $_{ft}$			0.087** (0.039)	-0.208*** (0.070)
Average CDS $_{ft}$			0.179*** (0.007)	0.077*** (0.007)
Debt coming due $_{ft}$			-0.462 (0.363)	0.060 (0.243)
Log assets $_{ft}$			0.121*** (0.004)	0.132*** (0.016)
Firm FE		✓		✓
Rating FE	✓		✓	
Time FE	✓	✓	✓	✓
Observations	20,806	20,806	20,806	20,806
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 firm-level dbr as constructed in Section 4.4. The outcome variable is a time-varying measure of firm's resilience, which is constructed as the beta of a firm's CDS to the CDX index. 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.

Table 9: Event analysis: Equity and CDS returns upon issuance

Panel (a): Low relative credit spread

	$r_{equity,ft}^e$			$r_{enterprise,ft}^e$		ΔCDS_{ft}^e	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}[LowCS]_{fnt}$		0.078** (0.033)	0.082** (0.033)	0.054** (0.023)	0.056** (0.023)	0.0003 (0.001)	0.001 (0.001)
$Issuance_{ft}$		1.018 (1.020)	2.995 (2.028)	0.417 (0.715)	2.598* (1.416)	-0.014 (0.032)	-0.090 (0.063)
$Average\ CDS_{f,t-1}$		0.018 (0.023)	0.004 (0.028)	0.019 (0.016)	0.017 (0.020)	-0.002*** (0.001)	-0.003*** (0.001)
$Tobin's\ Q_{f,t-1}$		-0.013 (0.012)	-0.069*** (0.024)	-0.006 (0.009)	-0.047*** (0.017)	0.001** (0.0004)	-0.001 (0.001)
Constant	0.001 (0.016)	-0.051 (0.040)		-0.045 (0.028)		0.002 (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): Low demand-based risk

	$r_{equity,ft}^e$			$r_{enterprise,ft}^e$		ΔCDS_{ft}^e	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}[LowDBR]_{fnt}$		-0.066 (0.075)	-0.041 (0.088)	-0.029 (0.053)	-0.022 (0.062)	-0.005** (0.002)	-0.005** (0.003)
$Issuance_{ft}$		0.066 (0.771)	2.932** (1.386)	-0.032 (0.551)	2.186** (0.986)	0.014 (0.023)	-0.098** (0.040)
$Average\ CDS_{f,t-1}$		-0.044** (0.021)	-0.035 (0.027)	-0.017 (0.015)	-0.002 (0.019)	-0.006*** (0.001)	-0.005*** (0.001)
$Tobin's\ Q_{f,t-1}$		-0.0004 (0.009)	-0.057*** (0.019)	0.002 (0.007)	-0.038*** (0.013)	-0.0003 (0.0003)	-0.0004 (0.001)
Constant	0.003 (0.015)	0.108 (0.082)		0.042 (0.059)		0.009*** (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 . All continuous variables are winsorized at the 1st and 99th percentiles.

Table 10: Impact of prior holdings on holdings change after issuance

	$\Delta\omega_{it}(n)$: Change in portfolio weight		
	(1)	(2)	(3)
$issuance_t(n) \times \omega_{i,t-1}(n)$	0.160*** (0.001)	0.158*** (0.001)	0.183*** (0.001)
$issuance_t(n)$	0.002*** (0.00001)	0.002*** (0.00001)	0.002*** (0.00001)
$\omega_{i,t-1}(n)$	-0.009*** (0.0001)	-0.025*** (0.0002)	0.001*** (0.0001)
Fund FE	✓	✓	
Quarter FE	✓	✓	
Fund \times Quarter FE			✓
Bond Type FE		✓	✓
Observations	6,113,647	6,113,647	6,113,647
R ²	0.090	0.105	0.401
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. The dependent variable $\Delta\omega_{it}(n)$ is the fund portfolio weights change in a specific bond type n at quarter t . $\omega_{it}(n)$ 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 $issuance_t(n)$ and $\omega_{i,t-1}(n)$. $issuance_t(n)$ is the total net issuance at quarter t normalized by total amount of outstanding at quarter $t - 1$ for bond type n . Data is quarterly from 2003 Q1 to 2023 Q4. All variables are winsorized at 1st and 99th percentiles.

Table 11: Impact of negative shocks on new investors share

	<i>NewInvestors_{ft}</i> : share of new investors in new bond issues			
	(1)	(2)	(3)	(4)
<i>Average CDS_{ft}</i>	-1.071*** (0.312)	-2.031*** (0.308)	-1.104** (0.459)	-1.056** (0.505)
<i>CDX_t</i>	-2.971*** (0.846)			
<i>Issuance_{ft}</i>	166.145*** (6.687)	166.205*** (6.239)	169.282*** (6.336)	115.383*** (7.365)
<i>Tobin's Q_{f,t-1}</i>	-0.273*** (0.076)	-0.109 (0.071)	-0.128* (0.071)	-0.261*** (0.095)
<i>Average CS_{f,t-1}</i>			-1.075*** (0.395)	0.688 (0.433)
Constant	45.203*** (0.591)			
Quarter FE		✓	✓	✓
Firm FE				✓
Observations	4,045	4,045	4,045	4,045
R ²	0.137	0.280	0.281	0.642
<i>Note:</i>			*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 issuance events from 2003 Q1 to 2023 Q4. The outcome variable *share_new_{ft}* is the fraction of number of new investors holding the newly issued bonds at quarter end. 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. All variables are winsorized at 1st and 99th percentiles.

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A Notation

We notate bond types as $n = 1, 2, \dots, N$, individual investors as $i = 1, \dots, I$, investor groups (Mutual Funds, Life Insurers, Property & Casualty Insurers) as g , investor categories (IG/Long MFs, IG/Short MFs, HY/Long MFs, HY/Short MFs, Life Insurers, P&C Insurers) as $c = 1, \dots, C$, and factors as $k = 1, \dots, K$.

Internet Appendix: Additional Tables and Proofs²⁷

A 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 especially from the WRDS link, cusips and string match, and to deal with duplicates.

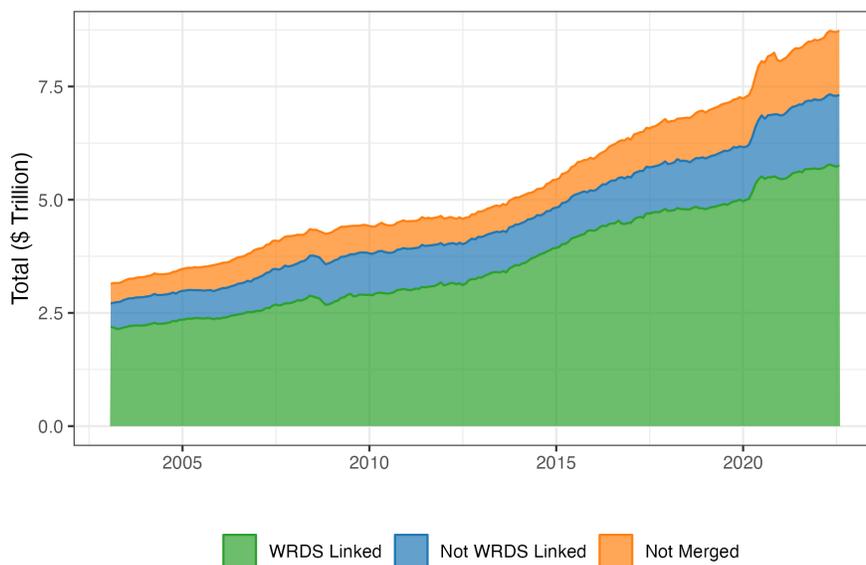
Panel (a) of Figure A.1 the share of the total amount outstanding of corporate bonds merged using only the WRDS bond returns link table and our extra merge. As the end of 2022, WRDS link was able to successfully link 66% of the almost \$9 trillion of bonds outstanding. Our final merge covers instead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

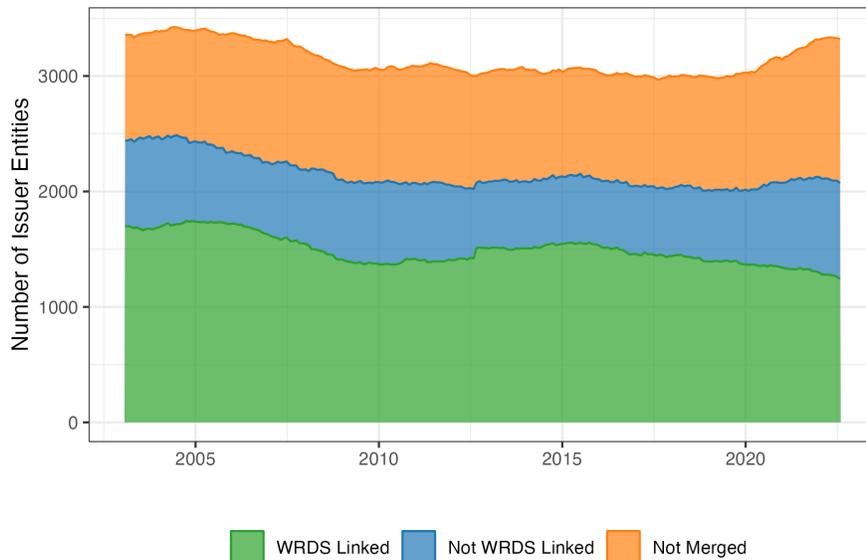
²⁷Mota, Lira, and Kerry Siani, Internet Appendix to “Financially Sophisticated Firms: A Demand-Based Approach to Corporate Financing.”

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 A.1: Corporate bond coverage merged with Compustat



(a) Amount outstanding merged



(b) Issuer entities merged

Note: This figure shows the amount outstanding (number of issuers) 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.

B Classification and consolidation of bond types

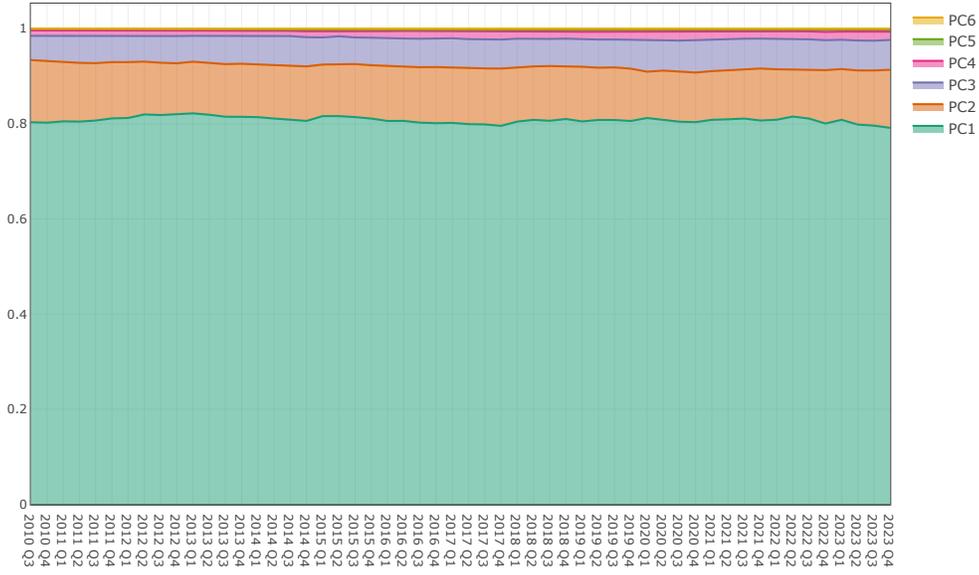
In an attempt to quantify the heterogeneity of bond structure in a tractable way, we construct a measure of unique bond type based on five dimensions: credit rating, time-to-maturity, issuance size, covenants, and redemption option. There should be 72 unique bond types in total based on our specifications. 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 B.1 presents the distribution of number of unique corporate bonds in each bond type.

Table B.1: Summary of bond types

	bond_type_id	Average # bonds	10th Percentile	Median	90th Percentile	bond_type_id	Average # bonds	10th Percentile	Median	90th Percentile
1	HY_0y3y_0m500m.TRUE.N	4,194	205	2,872	10,979	A_0y3y_500mm.FALSE.Y	199	46	212	313
2	HY_0y3y_0m500m.TRUE.Y	2,594	66	604	9,430	A_0y3y_0m500m.FALSE.Y	169	109	171	214
3	HY_3y10y_0m500m.TRUE.N	1,694	196	987	4,428	HY_10yy_0m500m.TRUE.N	156	83	140	273
4	A_0y3y_0m500m.TRUE.N	1,496	433	950	3,069	HY_3y10y_0m500m.FALSE.N	144	104	141	189
5	HY_3y10y_0m500m.TRUE.Y	1,477	343	648	4,498	HY_0y3y_0m500m.FALSE.N	142	107	136	191
6	HY_3y10y_0m500m.FALSE.Y	923	693	824	1,363	HY_3y10y_500mm.TRUE.Y	141	41	166	223
7	A_3y10y_0m500m.TRUE.N	876	625	868	1,093	HY_0y3y_500mm	139	49	119	231
8	BBB_3y10y_0m500m.FALSE.Y	690	650	694	726	A_0y3y_0m500m.FALSE.N	133	39	65	378
9	BBB_3y10y_500mm.FALSE.Y	564	190	488	1,128	A_3y10y_500mm.TRUE.N	133	64	139	226
10	A_10yy_0m500m.TRUE.Y	551	434	546	677	A_10yy_0m500m.FALSE.N	133	29	154	224
11	A_3y10y_0m500m.TRUE.Y	496	274	376	956	A_3y10y_500mm.TRUE.Y	133	41	117	241
12	A_10yy_0m500m.FALSE.Y	467	322	452	651	BBB_10yy_0m500m.TRUE.N	130	92	124	183
13	BBB_10yy_0m500m.FALSE.Y	462	391	426	590	A_3y10y_0m500m.FALSE.N	120	61	89	269
14	HY_3y10y_500mm.FALSE.Y	438	170	476	727	BBB_10yy_0m500m.FALSE.N	119	46	132	185
15	A_3y10y_500mm.FALSE.Y	424	206	446	657	BBB_3y10y_0m500m.FALSE.N	111	66	100	165
16	BBB_10yy_500mm	392	138	261	856	BBB_0y3y_0m500m.TRUE.Y	102	46	74	198
17	HY_0y3y_0m500m.FALSE.Y	349	249	352	452	BBB_0y3y_0m500m.FALSE.N	100	57	74	228
18	A_10yy_500mm.FALSE.Y	344	90	312	690	A_0y3y_500mm.TRUE.Y	95	10	50	215
19	BBB_0y3y_0m500m.FALSE.Y	323	228	335	384	BBB_3y10y_500mm.TRUE.Y	84	16	45	186
20	A_10yy_0m500m.TRUE.N	316	207	334	401	HY_10yy_500mm	83	63	79	106
21	A_3y10y_0m500m.FALSE.Y	313	270	316	353	A_10yy_500mm.TRUE.Y	76	23	53	162
22	BBB_3y10y_0m500m.TRUE.N	290	170	228	491	A_0y3y_500mm.FALSE.N	74	22	66	128
23	HY_10yy_0m500m.FALSE.Y	269	139	230	433	A_3y10y_500mm.FALSE.N	55	6	58	96
24	BBB_0y3y_0m500m.TRUE.N	260	145	214	504	HY_10yy_0m500m.FALSE.N	55	17	54	94
25	HY_10yy_0m500m.TRUE.Y	243	100	244	364	HY_3y10y_500mm.N	51	28	39	93
26	BBB_3y10y_0m500m.TRUE.Y	238	136	162	489	BBB_3y10y_500mm.N	51	29	50	73
27	A_0y3y_500mm.TRUE.N	234	125	215	376	A_10yy_500mm.N	42	25	45	52
28	A_0y3y_0m500m.TRUE.Y	218	101	193	277	BBB_0y3y_500mm.TRUE.Y	40	3	12	105
29	BBB_0y3y_500mm.FALSE.Y	205	43	141	432	BBB_0y3y_500mm.FALSE.N	34	16	30	56
30	BBB_10yy_0m500m.TRUE.Y	202	96	125	369	BBB_0y3y_500mm.TRUE.N	30	13	29	51

[1] *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.

Figure B.1: Variation in orthogonalized flows explained by principal components

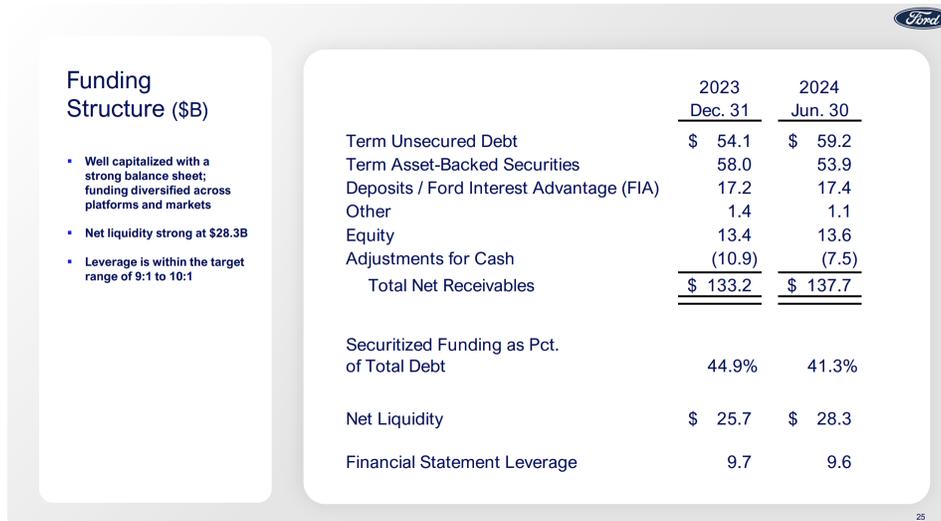


Note: This figure shows the proportion of variation explained by the principal components at each point in time, based on the cross-sectional PCA regression specified in Equation (28): $S'_{t-1} \times f^\perp = \alpha + \delta_{t-1}F + u$. Here, $S_{t-1} \in \mathbb{R}^{C \times N}$ denotes the time-varying matrix 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 $f_{ct}^\perp = \frac{\sum_{i \in c} f_{it}^\perp \cdot AUM_{i,t-1}}{AUM_{c,t-1}}$. $F \in \mathbb{R}^{1 \times T}$ 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.

C Extra data description

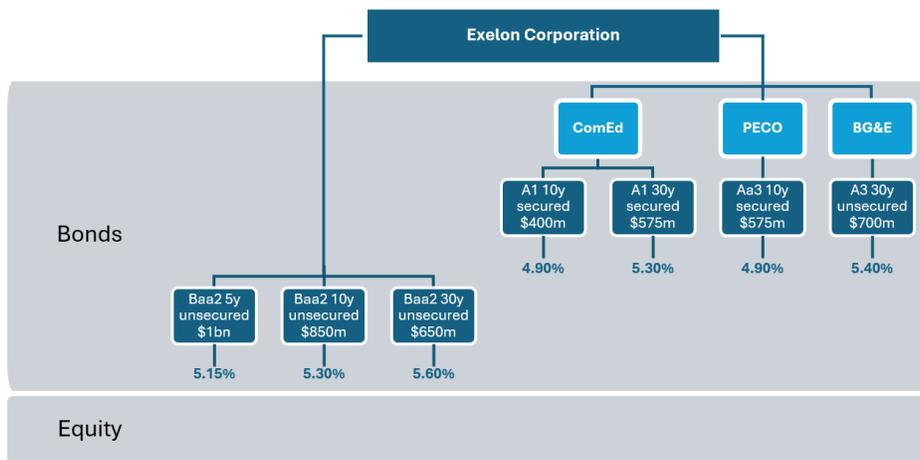
C.1 Data example

Figure C.1: Slide from Ford Investor Deck



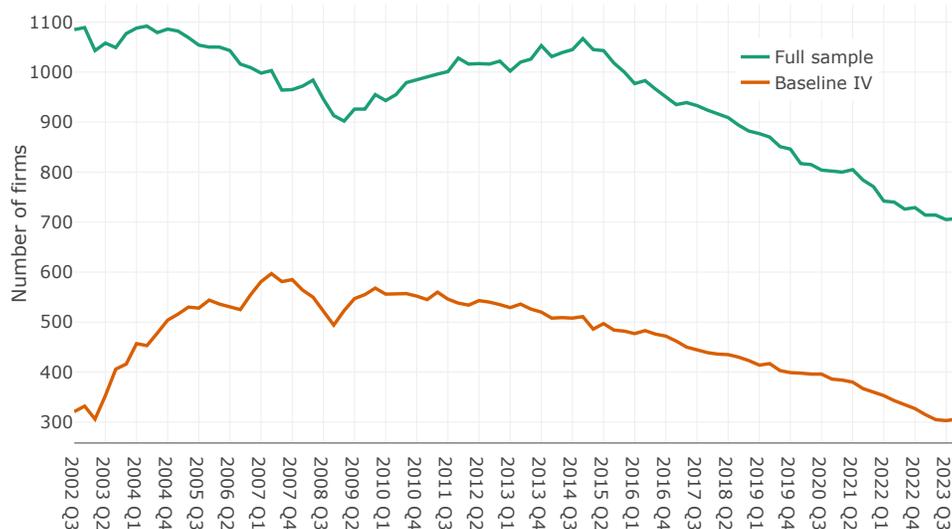
Note: This shows a screenshot from the Ford Fixed Income Presentation at SMBC Auto Summit (Sumitomo Mitsui Banking Corporation) in September 2024. Source: Ford website.

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



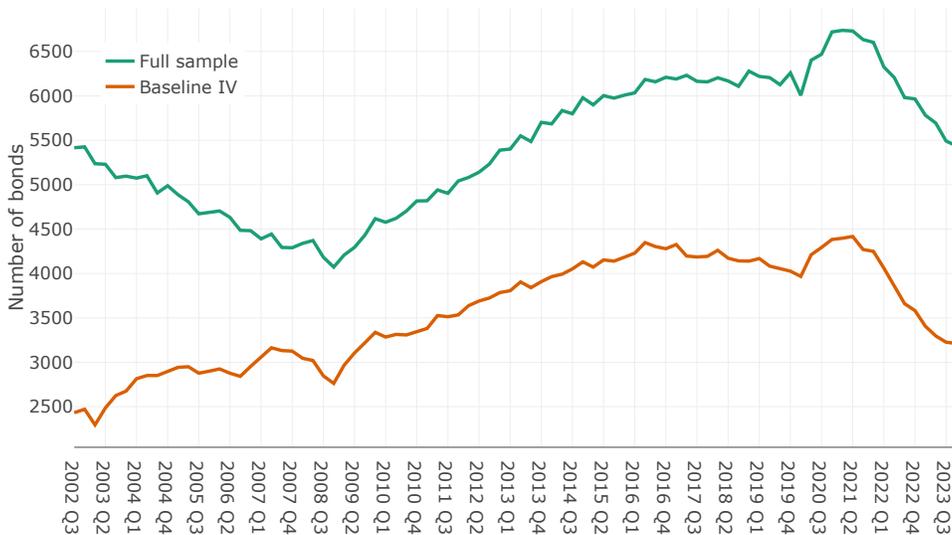
Note: This figure shows the debt issued by Exelon Corporation and its subsidiaries (i.e., Commonwealth Edison, PECO Energy, and Baltimore Gas & Electric) in 2023, conditional on bonds greater than \$400 million at issuance. Coupon rates are presented below.

Figure C.3: Number of firms in the sample over time



Note: This figure shows the number of unique firms in our final sample over time. The upper line represents the full merged Mergent FISD–Compustat dataset, and the lower line shows our baseline IV sample, conditional on firms with non-null CDS spreads.

Figure C.4: Number of bonds in the sample over time



Note: This figure shows the number of unique bonds in our final sample over time. The upper line represents the full merged Mergent FISD–Compustat dataset, and the lower line shows our baseline IV sample, conditional on bonds with non-null CDS spreads.

C.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 $\frac{param_{ibt}}{amt_{out}_{bt}}$ at $[0, 1]$ and 99th percentile for CRSP and NAIC corporate bond holdings.
2. Truncate net flows f_{it}^g at 1st and 99th percentiles, separately for $g \in [\text{MFs, Life insurers, P\&C insurers}]$. Specifically,

$$f_{iq}^{MF} = \frac{AUM_{iq} - (1 + R_{iq}) \times AUM_{i,q-1}}{AUM_{i,q-1}} \quad (36)$$

$$f_{iq}^{INS} = \frac{OperatingIncome_{iq} - OperatingIncome_{i,q-4}}{AUM_{i,q-4}} \quad (37)$$

3. Winsorize R_{it}^g at 1st and 99th percentiles, separately for $g \in [\text{MFs, Life insurers, P\&C insurers}]$. This variable is used when computing the fund-quarter level orthogonalized flows as constructed in Equation (25).
4. Truncate fund-bond type quarter level $\frac{param_{it-1}(n)}{amt_{out_{t-1}}(n)}$ at 99% percentiles for both the aggregation of $z_t^{cs}(n)$ (as constructed in Equation (27)) and $z_t^{dbr}(n)$ (as constructed in Equation (31)).

Table C.1: 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	≥ 10 years	< 500 million	≥ 500 million	True	False	Yes	No
All Investors	38.18	35.08	44.33	37.15	28.49	40.33	41.62	45.41	35.01	34.10	39.78	40.36	30.16
IG/Long MFs	7.36	7.94	9.32	3.09	5.91	7.12	8.68	4.74	8.22	7.37	7.34	7.28	7.22
IG/Short MFs	1.69	2.01	2.10	0.33	4.54	1.47	0.04	1.15	1.86	2.11	1.54	1.52	2.39
Other/Long MFs	6.68	0.75	2.76	23.63	2.95	9.83	3.24	7.25	6.30	5.67	7.09	7.84	2.85
Other/Short MFs	0.47	0.01	0.10	2.01	0.52	0.69	0.02	0.42	0.49	0.40	0.50	0.54	0.12
PC Insurers	3.34	4.18	3.63	1.43	3.66	4.18	1.41	3.82	3.15	3.24	3.38	3.37	3.01
Life Insurers	18.63	20.18	26.42	6.65	10.91	17.04	28.22	28.03	14.99	15.31	19.92	19.81	14.57

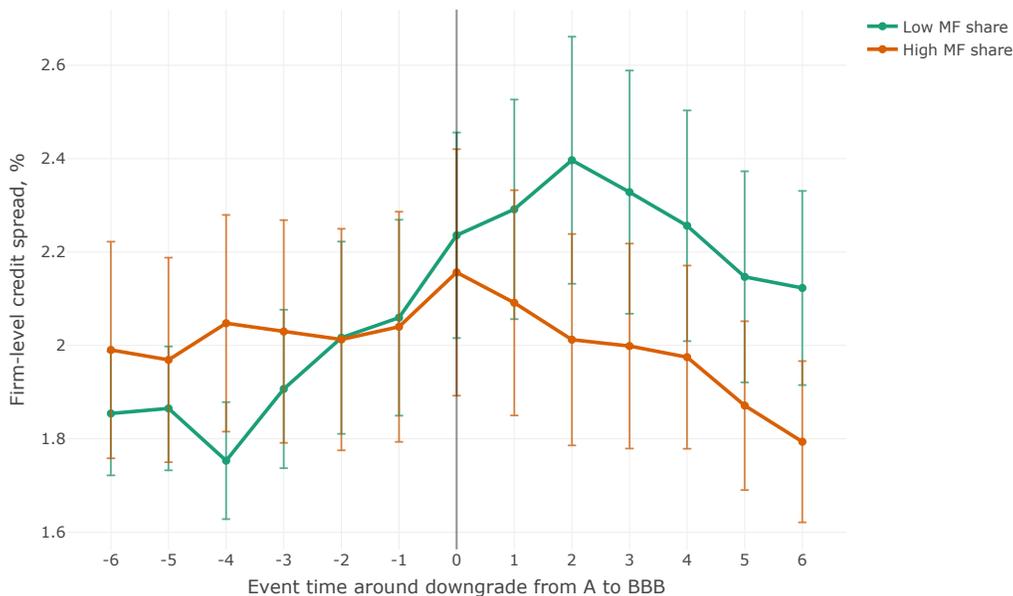
Note: This table presents the share of corporate bonds outstanding for different investor categories, segmented by the five dimensions of bond type characteristics. The share of amount outstanding is computed by dividing the total amount outstanding of corporate bonds with a given characteristic by the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

Table C.2: Share of firms with multiple issuer IDs within industry

Industry	Share of firms (%)
Utilities	40.26
Transportation and Warehousing	34.68
Finance	33.33
Real Estate	29.29
Mining, Oil and Gas Extraction	25.64
Information	25.24
Manufacturing	23
Retail Trade	20.69
Professional, Scientific, and Technical Services	20.41
Wholesale Trade	17.50
Full Sample	24.63

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 2003 Q1 to 2023 Q4.

Figure C.5: Firm 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.

D Model proofs

D.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 $r = R - 1$.

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

$$r(n) = \mu(n) + \boldsymbol{\beta}(n)^\top \mathbf{f} + \epsilon_r(n) \quad (38)$$

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

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

$$W'_i = W_{i0}[\omega_i^f + \omega_i^\top \mathbf{R} - \theta_i^\top \mathbf{f}].$$

or

$$\frac{W'_i}{W_{i0}} = 1 + \omega_i^\top \mathbf{r} - \theta_i^\top \mathbf{f}.$$

Investors choose portfolio weights to maximize

$$\max_{\omega_i^f \in \mathbb{R}, \omega_i \in \mathbb{R}^N} \mathbb{E}[W'_i] - \frac{\gamma_i}{2} \text{Var}(W'_i), \quad (39)$$

$$\text{s.t. } \mathbf{1}^\top \omega_i + \omega_i^f = 1 \quad (40)$$

$$\omega_{fi} \geq 0 \text{ and } \omega_i \geq \mathbf{0}. \quad (41)$$

Define the factor-asset covariance

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

Using the above,

$$\text{Var}(W'_i) = W_{i0}^2 \left[\underbrace{\omega_i^\top \Sigma_r \omega_i}_{(1 \times N)(N \times N)(N \times 1)} - 2 \underbrace{\omega_i^\top \mathbf{h} \theta_i}_{(1 \times N)(N \times K_r)(K_r \times 1)} + \underbrace{\theta_i^\top \Sigma_f \theta_i}_{(1 \times K_r)(K_r \times K_r)(K_r \times 1)} \right].$$

The expectation and variance of wealth is thus:

$$\mathbb{E}[W'_i] = W_{i0} \left[1 + \mathbb{E}[\mathbf{r}]^\top \omega_i \right],$$

$$\text{Var}(W'_i) = W_{i0}^2 \left[\omega_i^\top \Sigma_r \omega_i - 2 \omega_i^\top \mathbf{h} \theta_i + \theta_i^\top \Sigma_f \theta_i \right].$$

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

$$\begin{aligned} \mathcal{L}(\omega_i, \lambda_i, \lambda_{if}) = & W_{i0} \left[1 + \mu^\top \omega_i \right] - \frac{\gamma_i W_{i0}^2}{2} \left[\omega_i^\top \Sigma_r \omega_i - 2 \omega_i^\top \mathbf{h} \theta_i + \theta_i^\top \Sigma_f \theta_i \right] \\ & + \lambda_i^\top \omega_i + \lambda_{if} \left[1 - \mathbf{1}^\top \omega_i \right]. \end{aligned}$$

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

$$\mathbf{1}^\top \omega_i \leq 1.$$

From the agent's first order condition, we have

$$\frac{\partial \mathcal{L}}{\partial \omega_i} = W_{i0} \boldsymbol{\mu} - \gamma_i W_{i0}^2 (\Sigma_r \omega_i - \mathbf{h} \theta_i) + \lambda_i - \lambda_{if} \mathbf{1} = 0$$

and the complementary slack conditions

$$\lambda_{i,k} \omega_{i,k} = 0, \quad \lambda_{i,k} \geq 0, \quad \omega_{i,k} \geq 0, \quad \lambda_{if} [1 - \mathbf{1}^\top \omega_i] = 0, \quad \lambda_{if} \geq 0, \quad 1 - \mathbf{1}^\top \omega_i \geq 0.$$

Hence, the optimal portfolio choice is

$$\boxed{\omega_i^* = \frac{1}{\gamma_i W_{i0}} \Sigma_r^{-1} \left[\boldsymbol{\mu} + \gamma_i W_{i0} \mathbf{h} \theta_i + \frac{1}{W_{i0}} (\lambda_i + \lambda_{if} \mathbf{1}) \right]} \quad (42)$$

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

$$\Sigma_r^{-1} = \Sigma_{\epsilon_r}^{-1} - \Sigma_{\epsilon_r}^{-1} \boldsymbol{\beta}^\top (\Sigma_f^{-1} + \boldsymbol{\beta} \Sigma_{\epsilon_r}^{-1} \boldsymbol{\beta}^\top)^{-1} \boldsymbol{\beta} \Sigma_{\epsilon_r}^{-1} \quad (43)$$

Plugging into Equation 42, we get:

$$\boxed{\omega_i^* = \frac{1}{\gamma_i W_{i0}} \Sigma_{\epsilon_r}^{-1} \left[\boldsymbol{\mu} + \gamma_i W_{i0} \mathbf{h} \theta_i + \frac{1}{W_{i0}} (\lambda_i - \lambda_{if} \mathbf{1}) - \boldsymbol{\beta}^\top \boldsymbol{\kappa}_i \right]} \quad (44)$$

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

We can then write optimal portfolio choice as:

$$\boxed{\omega_i^* = \frac{1}{\gamma_i W_{i0}} \Sigma_{\epsilon_r}^{-1} \left[\tilde{\boldsymbol{\mu}}_i - \boldsymbol{\beta}^\top \boldsymbol{\kappa}_i \right]} \quad (45)$$

D.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 $\mathbf{q}^\top \mathbf{1}$, where $\mathbf{q} \in \mathbb{R}^N$ 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 cost associated with issuing each bond type n . This cost 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 demand-based shock to bond n . We assume there are K_ι factors, $\mathbf{g} \in \mathbb{R}^{K_\iota}$, driving investor demand and a $\epsilon_\iota(n)$ an idiosyncratic cost. The demand-based shock can be formally expressed as

$$\iota(n) = \bar{\iota}(n) + \boldsymbol{\delta}(\mathbf{g})^\top \mathbf{g} + \epsilon_\iota(n) \quad (46)$$

where $\mathbb{E}[\mathbf{g}] = \mathbf{0}$, $\mathbb{E}[\epsilon_\iota] = 0$, $Cov(\boldsymbol{\iota}) = \Sigma_\iota$, $Cov(\mathbf{g}) = \Sigma_g$, and $Cov(\epsilon_\iota) = \Sigma_{\epsilon_\iota} = \text{diag}(\sigma_{\epsilon_\iota}^2)$. 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 financial fragility. Let $\gamma_f > 0$ be the firm-specific cost of issuing bonds. It chooses its debt structure to maximize

$$\max_{\mathbf{q} \in \mathbb{R}^N} \mathbb{E}[D + \mathbf{q}^\top (\mathbf{1} - \mathbf{R})] - \frac{\gamma_f}{2} \mathbf{q}^\top \Sigma_\iota \mathbf{q} \quad (47)$$

$$\text{s.t. } \mathbf{q}^\top \mathbf{1} \geq c, \mathbf{q} \geq \mathbf{0} \quad (48)$$

$$\mathbf{q}^\top (\mathbf{1} - \mathbf{R}(s)) + (D - c) \geq 0 \forall \text{ all states } s, \quad (49)$$

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

$$\mathbf{q}^* = \frac{1}{\gamma_f} \Sigma_\iota^{-1} (\mathbf{1} - \mathbb{E}[\mathbf{R}]) = -\frac{1}{\gamma_f} \Sigma_\iota^{-1} \boldsymbol{\mu} \quad (50)$$

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

It is useful to note that \mathbf{q}^* is linear in $\boldsymbol{\mu}$ and $\boldsymbol{\delta}$, the demand-based shock loading on the common factor. To see this, we can use the Woodbury matrix identity,

$$\Sigma_\iota^{-1} = \Sigma_{\epsilon_\iota}^{-1} - \Sigma_{\epsilon_\iota}^{-1} \boldsymbol{\delta}^\top \left(\Sigma_g^{-1} + \boldsymbol{\delta} \Sigma_{\epsilon_\iota}^{-1} \boldsymbol{\delta}^\top \right)^{-1} \boldsymbol{\delta} \Sigma_{\epsilon_\iota}^{-1} \quad (51)$$

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

$$\mathbf{q}_s^* = -\frac{1}{\gamma_f} \Sigma_{\epsilon_t}^{-1} \left[\boldsymbol{\mu} - \boldsymbol{\delta}^\top \boldsymbol{\kappa}_f \right]. \quad (52)$$

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

$$q_s^*(n) = -\frac{1}{\gamma_f \sigma_{\epsilon_t}^2(n)} \left[\mu(n) - \delta^\top(n) \boldsymbol{\kappa}_f \right] \quad (53)$$

D.3 Equilibrium in the Bond Market

Aggregate Demand

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

$$\mathbf{q}_d^* = \sum_i W_{i0} \omega_i^* \quad (54)$$

$$= \frac{1}{\gamma_d} \sum_i W_{i0} \Sigma_{\epsilon_r}^{-1} \left[\boldsymbol{\mu} + \gamma_d \mathbf{h} \boldsymbol{\theta}_i + \frac{1}{W_{i0}} \tilde{\lambda}_i - \boldsymbol{\beta}^\top \boldsymbol{\kappa}_i \right] \quad (55)$$

$$= \frac{1}{\gamma_d} \Sigma_{\epsilon_r}^{-1} \left[\boldsymbol{\mu} W_0 + \gamma_d \mathbf{h} \sum_i W_{i0} \boldsymbol{\theta}_i + \sum_i \tilde{\lambda}_i - \boldsymbol{\beta}^\top \sum_i W_{i0} \boldsymbol{\kappa}_i \right] \quad (56)$$

$$= \frac{W_0}{\gamma_d} \Sigma_{\epsilon_r}^{-1} \left[\boldsymbol{\mu} + \gamma_d \mathbf{h} \bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}} \right] \quad (57)$$

where $W_0 = \sum_i W_{oi}$ is the total investable wealth in the economy, $\tilde{w}_i = \frac{W_{oi}}{W_0}$ 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 \mathbf{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:

$$q_d^*(n) = \frac{W_0}{\gamma_d \sigma_{\epsilon_r}^2(n)} \left[\mu(n) + \gamma_d \mathbf{h}(n) \bar{\boldsymbol{\theta}} + \lambda(n) - \boldsymbol{\beta}^\top(n) \bar{\boldsymbol{\kappa}} \right] \quad (58)$$

Market Clearing

Equate supply and demand:

$$\mathbf{q}_s^* = \mathbf{q}_d^* \quad (59)$$

$$\implies -\frac{1}{\gamma_f} \Sigma_{\epsilon_t}^{-1} [\boldsymbol{\mu} - \boldsymbol{\delta}^\top \boldsymbol{\kappa}_f] = \frac{W_0}{\gamma_d} \Sigma_{\epsilon_r}^{-1} [\boldsymbol{\mu} + \gamma_d \mathbf{h} \bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}}] \quad (60)$$

$$\implies \boldsymbol{\mu} = \left(\frac{1}{\gamma_f} \Sigma_{\epsilon_t}^{-1} + \frac{W_0}{\gamma_d} \Sigma_{\epsilon_r}^{-1} \right)^{-1} \left[\frac{1}{\gamma_f} \Sigma_{\epsilon_t}^{-1} \boldsymbol{\delta}^\top \boldsymbol{\kappa}_f - \frac{W_0}{\gamma_d} \Sigma_{\epsilon_r}^{-1} (\gamma_d \mathbf{h} \bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}} - \boldsymbol{\beta}^\top \bar{\boldsymbol{\kappa}}) \right] \quad (61)$$

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

$$\mathbf{q}_s^*(n) = \mathbf{q}_d^*(n) \quad (62)$$

$$\implies \frac{W_0}{\gamma_d \sigma_r^2(n)} [\boldsymbol{\mu}(n) + \gamma_d \mathbf{h}(n)^\top \bar{\boldsymbol{\theta}} + \bar{\boldsymbol{\lambda}}(n) - \boldsymbol{\beta}(n)^\top \bar{\boldsymbol{\kappa}}] = -\frac{1}{\gamma_f \sigma_t^2(n)} [\boldsymbol{\mu}(n) - \boldsymbol{\delta}(n)^\top \boldsymbol{\kappa}_f] \quad (63)$$

$$\implies \boldsymbol{\mu}(n) = \left(\frac{W_0}{\gamma_d \sigma_r^2(n)} + \frac{1}{\gamma_f \sigma_t^2(n)} \right)^{-1} \left[\frac{W_0}{\gamma_d \sigma_r^2(n)} (-\gamma_d \bar{\boldsymbol{\theta}}^\top \mathbf{h}(n) - \bar{\boldsymbol{\lambda}}(n) + \bar{\boldsymbol{\kappa}}^\top \boldsymbol{\beta}(n)) + \frac{1}{\gamma_f \sigma_t^2(n)} \boldsymbol{\delta}(n)^\top \boldsymbol{\kappa}_f \right] \quad (64)$$

$$\implies \boldsymbol{\mu}(n) = B_\theta(n) \cdot \bar{\boldsymbol{\theta}}^\top \mathbf{h}(n) + B_\lambda(n) \cdot \bar{\boldsymbol{\lambda}}(n) + B_\beta(n) \cdot \boldsymbol{\beta}(n) + B_\delta(n) \cdot \boldsymbol{\delta}(n) \quad (65)$$

where

$$A(n) = \left(\frac{W_0}{\gamma_d \sigma_r^2(n)} + \frac{1}{\gamma_f \sigma_t^2(n)} \right)^{-1} \quad (66)$$

$$B_\theta(n) = -A(n) \cdot \frac{W_0}{\sigma_r^2(n)} \quad (67)$$

$$B_\lambda(n) = -A(n) \cdot \frac{W_0}{\gamma_d \sigma_r^2(n)} \quad (68)$$

$$B_\beta(n) = A(n) \cdot \frac{W_0}{\gamma_d \sigma_r^2(n)} \bar{\boldsymbol{\kappa}}^\top \quad (69)$$

$$B_\delta(n) = A(n) \cdot \frac{1}{\gamma_f \sigma_t^2(n)} \boldsymbol{\kappa}_f \quad (70)$$

E Robustness

E.1 Simple OLS

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

	<i>issuance_{f,t}(n)</i> : Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r$: Relative credit spread	-0.012 (0.008)	-0.021** (0.009)			-0.012 (0.008)	-0.021** (0.009)
$dbr_{t-1}(n)$: Demand-based risk			0.002 (0.058)	0.010 (0.058)	0.002 (0.058)	0.010 (0.058)
Tobin's $Q_{f,t-1}$	0.071* (0.043)		0.071 (0.043)		0.071 (0.043)	
Leverage $_{f,t-1}$	-0.190*** (0.044)		-0.190*** (0.044)		-0.190*** (0.044)	
Debt coming due $_{f,t-1}$	1.570*** (0.249)		1.570*** (0.249)		1.570*** (0.249)	
Average CDS $_{f,t-1}$	-0.668** (0.264)		-0.668** (0.263)		-0.668** (0.263)	
Log assets $_{f,t-1}$	-0.069*** (0.011)		-0.069*** (0.011)		-0.069*** (0.011)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
Observations	133,066	133,066	133,066	133,066	133,066	133,066

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 (24). We winsorize $cs_{f,t-1}^r$, Tobin's Q , leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level.

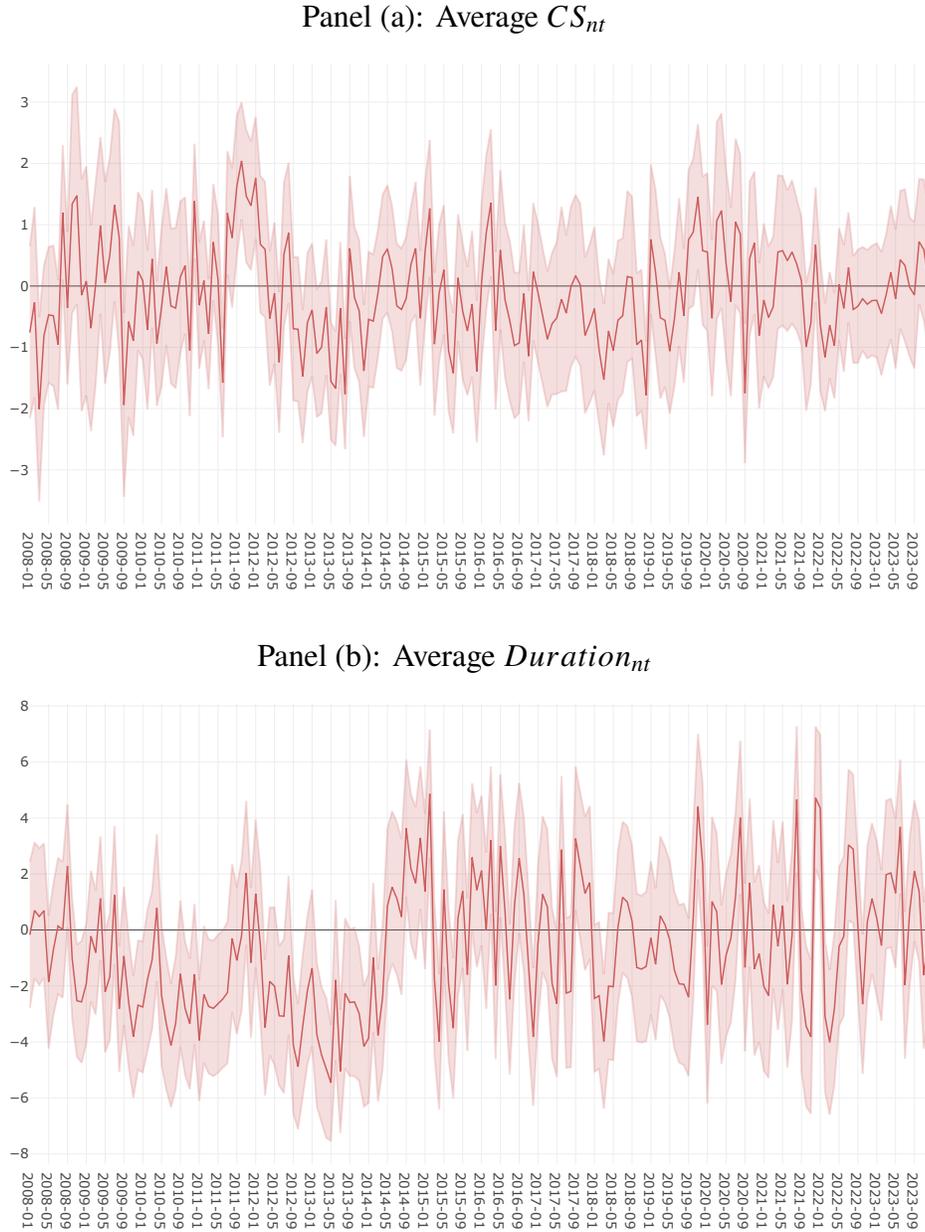
E.2 Ensuring the instrument is uncorrelated with bond characteristics

The concern raised by Haddad et al. (2025) is that flows could correlate with bond characteristics associated with risk loadings, potentially causing endogeneity in instruments based on net fund flows. They show in that by not accounting for characteristics in the flows, a portfolio of long-short equal weighted portfolios based on whether the their instrument Z_{nt}^{HHHKL} is above or below median is correlated with credit rating and duration factors, while when they residualize the instrument for duration and maturity by time fixed effects, it suffers less so from the covariance.

In our analysis, these exact dimensions—duration and maturity—are crucial sources of variation we aim to examine, so we do not want to residualize them. However, we still need to ensure that our instrument, denoted Z_{nt}^{MS} here, does not correlate systematically with risk factors. To test this, we construct long-short portfolios based on whether mutual fund flows in our instrument are above or below median values. Importantly, our analysis is conducted at the aggregated bond-type level (rather than for individual bonds), enabling consistent comparisons across time.

We illustrate these tests in Figure E.1, showing the differences in prior-period average credit spreads and duration between bonds in our “treated” (above median Z_{nt}^{MS}) and “control” (below median) groups. Our findings indicate that, in nearly all periods, differences in these characteristics between treated and control groups are statistically insignificant. This provides reassurance that our instrument satisfies the exclusion restriction, supporting its validity in our context.

Figure E.1: Test that treatment vs. control bonds are similar on ex-ante characteristics



Note: This figure reports the average difference in credit spreads and duration for High vs. Low Z_{nt}^{MS} groups, defined using the cross-sectional median of Z_{nt}^{MS} constructed from equation (27) for mutual funds at each point in time. Panel (a) shows the time series of the differences in credit spreads between the two sets of bonds, with 99% confidence intervals shaded; Panel (b) shows the corresponding plot for duration. The sample is at the an idiosyncratic level from January 2008 to December 2023, conditioning on bonds with at least 1 year remaining time-to-maturity in each period.

E.3 Mutual funds vs. insurance companies flows

Table E.2: Baseline IV using only flows from MFs

Panel A: First stage test for flow-based instruments						
	$cs_{f,t-1}^s(n)$		$dbr_{t-1}(n)$		$cs_{f,t-1}^r(n)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z_{t-1}^{cs}(n)$: Exogenous net flows	-0.047*** (0.006)	-0.061*** (0.007)			-0.038*** (0.007)	-0.041*** (0.008)
$z_{t-1}^{dbr}(n)$			0.475*** (0.004)	0.559*** (0.004)	-0.057*** (0.014)	-0.115*** (0.016)
<i>Tobin's</i> $Q_{f,t-1}$	0.001 (0.011)		0.012*** (0.003)		0.001 (0.011)	
<i>Leverage</i> f_{t-1}	0.002 (0.008)		0.014*** (0.002)		0.002 (0.008)	
<i>Debt coming due</i> f_{t-1}	-0.036 (0.044)		0.023* (0.012)		-0.038 (0.044)	
<i>Average CDS</i> f_{t-1}	-0.061 (0.063)		0.127*** (0.017)		-0.055 (0.063)	
<i>Log assets</i> f_{t-1}	-0.002 (0.002)		0.004*** (0.0005)		-0.002 (0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	<i>issuance</i> $f_t(n)$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r(n)$: Relative credit spread	-1.608** (0.666)	-1.266** (0.555)			-2.444*** (0.933)	-2.530** (0.987)
$dbr_{t-1}(n)$: Demand-based risk			-0.225* (0.123)	-0.266** (0.112)	-0.657*** (0.225)	-0.916*** (0.286)
<i>Tobin's</i> $Q_{f,t-1}$	0.071 (0.052)		0.074* (0.043)		0.080 (0.062)	
<i>Leverage</i> f_{t-1}	-0.189*** (0.046)		-0.186*** (0.044)		-0.175*** (0.048)	
<i>Debt coming due</i> f_{t-1}	1.509*** (0.269)		1.572*** (0.249)		1.483*** (0.290)	
<i>Average CDS</i> f_{t-1}	-0.766** (0.331)		-0.629** (0.264)		-0.702* (0.417)	
<i>Log assets</i> f_{t-1}	-0.072*** (0.011)		-0.069*** (0.011)		-0.072*** (0.011)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	6.32	42.41	290.77	2510.02	25.13	18.91
Observations	133,011	133,011	133,011	133,011	133,011	133,011
<i>Note:</i>	*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 as described in Equation 24 and Section 4.4. Standard errors are clustered at the firm level.

Table E.3: Baseline IV using only flows from insurers

Panel A: First stage test for flow-based instruments						
	$cs_{f,t-1}^r(n)$		$dbr_{t-1}(n)$		$cs_{f,t-1}^r(n)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z_{t-1}^{cs}(n)$: Exogenous net flows	-0.277*** (0.032)	-0.296*** (0.034)			-0.279*** (0.032)	-0.296*** (0.034)
$z_{t-1}^{dbr}(n)$			0.475*** (0.004)	0.559*** (0.004)	-0.084*** (0.014)	-0.143*** (0.015)
Tobin's $Q_{f,t-1}$	0.001 (0.011)		0.012*** (0.003)		0.001 (0.011)	
Leverage f_{t-1}	0.001 (0.008)		0.014*** (0.002)		0.002 (0.008)	
Debt coming due f_{t-1}	-0.037 (0.044)		0.022* (0.012)		-0.039 (0.044)	
Average CDS f_{t-1}	-0.058 (0.063)		0.128*** (0.017)		-0.050 (0.063)	
Log assets f_{t-1}	-0.002 (0.002)		0.004*** (0.0005)		-0.002 (0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{f,t}(n)$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r(n)$: Relative credit spread	-0.942** (0.373)	-0.443 (0.328)			-0.903** (0.366)	-0.418 (0.322)
$dbr_{t-1}(n)$: Demand-based risk			-0.226* (0.123)	-0.266** (0.112)	-0.383*** (0.135)	-0.373*** (0.136)
Tobin's $Q_{f,t-1}$	0.071 (0.047)		0.074* (0.043)		0.076 (0.047)	
Leverage f_{t-1}	-0.190*** (0.044)		-0.186*** (0.044)		-0.182*** (0.043)	
Debt coming due f_{t-1}	1.536*** (0.257)		1.572*** (0.249)		1.541*** (0.257)	
Average CDS f_{t-1}	-0.726** (0.284)		-0.628** (0.264)		-0.656** (0.282)	
Log assets f_{t-1}	-0.071*** (0.010)		-0.069*** (0.011)		-0.070*** (0.010)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	14.32	96.82	290.6	2510.11	89.52	102.04
Observations	133,055	133,055	133,055	133,055	133,055	133,055

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 as described in Equation 24 and Section 4.4. $issuance_{f,t}(n)$, $cs_{f,t-1}^r(n)$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level.

E.4 Retail mutual fund 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 by contemporaneous returns. That is, investors would need to have private information about firm fundamentals that lead to issuance in way that flows are not reflected in prices within a quarter.

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. Specifically, 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 E.4 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.

Table E.4: Baseline IV using only flows from retail MFs

Panel A: First stage test for flow-based instruments						
	$cs_{f,t-1}^r(n)$		$dbr_{t-1}(n)$		$cs_{f,t-1}^r(n)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z_{t-1}^{cs}(n)$: Exogenous net flows	-0.316*** (0.009)	-0.296*** (0.010)			-0.323*** (0.009)	-0.289*** (0.010)
$z_{t-1}^{dbr}(n)$			0.475*** (0.004)	0.559*** (0.004)	0.041*** (0.014)	-0.037** (0.015)
Tobin's $Q_{f,t-1}$	-0.001 (0.010)		0.012*** (0.003)		-0.001 (0.010)	
Leverage f_{t-1}	-0.001 (0.008)		0.014*** (0.002)		-0.002 (0.008)	
Debt coming due f_{t-1}	-0.030 (0.044)		0.023* (0.012)		-0.029 (0.044)	
Average CDS f_{t-1}	-0.122* (0.062)		0.127*** (0.017)		-0.127** (0.062)	
Log assets f_{t-1}	-0.002 (0.002)		0.004*** (0.0005)		-0.002 (0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{f,t}(n)$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r(n)$: Relative credit spread	-0.497*** (0.121)	-0.676*** (0.141)			-0.561*** (0.124)	-0.818*** (0.154)
$dbr_{t-1}(n)$: Demand-based risk			-0.226* (0.123)	-0.267** (0.112)	-0.325*** (0.125)	-0.477*** (0.123)
Tobin's $Q_{f,t-1}$	0.071 (0.044)		0.074* (0.043)		0.075* (0.045)	
Leverage f_{t-1}	-0.190*** (0.044)		-0.186*** (0.044)		-0.184*** (0.044)	
Debt coming due f_{t-1}	1.553*** (0.252)		1.572*** (0.249)		1.554*** (0.253)	
Average CDS f_{t-1}	-0.702*** (0.265)		-0.630** (0.264)		-0.649** (0.267)	
Log assets f_{t-1}	-0.070*** (0.010)		-0.069*** (0.011)		-0.070*** (0.010)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	83.84	417.73	291.43	2510.76	563.96	396.84
Observations	132,963	132,963	132,963	132,963	132,963	132,963
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 as described in Equation 24 and Section 4.4. $issuance_{f,t}(n)$, $cs_{f,t-1}^r(n)$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level.

E.5 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 : $MktShare_{i,s,q-4 \rightarrow q-1} = \frac{\sum_{t=q-4}^{q-1} DirectPremium_{i,s,t}}{\sum_{t=q-4}^{q-1} \sum_i DirectPremium_{i,s,t}}$, and then summing the unusual damage across states: $Exposure_{i,q} = \sum_{s \in i} UnusualWeatherDamage_{sq} \times MktShare_{i,s,q-4 \rightarrow q-1}$. 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 E.5 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.

Table E.5: Natural disaster IV

Panel A: First stage test for flow-based instruments						
	$cs_{f,t-1}^r(n)$		$dbr_{t-1}(n)$		$cs_{f,t-1}^r(n)$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Exposure_{t-1}(n)$: Exposure to disasters	0.224*** (0.028)	0.187*** (0.031)			0.225*** (0.028)	0.189*** (0.031)
z_{t-1}^{dbr}			0.668*** (0.007)	0.836*** (0.009)	-0.146*** (0.020)	-0.144*** (0.024)
Tobin's $Q_{f,t-1}$	0.001 (0.010)		0.003 (0.004)		0.001 (0.010)	
Leverage $_{f,t-1}$	0.001 (0.008)		0.018*** (0.003)		0.002 (0.008)	
Debt coming due $_{f,t-1}$	-0.026 (0.046)		0.028* (0.017)		-0.029 (0.046)	
Average CDS $_{f,t-1}$	0.165** (0.077)		0.226*** (0.028)		0.172** (0.077)	
Log assets $_{f,t-1}$	-0.001 (0.002)		-0.0004 (0.001)		-0.001 (0.002)	
Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{f,t}(n)$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r$: Relative credit spread	-0.931** (0.467)	-1.707** (0.697)			-0.868* (0.454)	-1.705** (0.696)
$dbr_{n,t-1}$: Demand-based risk			-0.546*** (0.163)	-0.547*** (0.135)	-0.736*** (0.203)	-0.837*** (0.202)
Tobin's $Q_{f,t-1}$	0.046 (0.048)		0.046 (0.047)		0.048 (0.048)	
Leverage $_{f,t-1}$	-0.177*** (0.066)		-0.163** (0.065)		-0.158** (0.067)	
Debt coming due $_{f,t-1}$	1.586*** (0.333)		1.618*** (0.331)		1.597*** (0.334)	
Average CDS $_{f,t-1}$	0.232 (0.422)		0.219 (0.383)		0.412 (0.434)	
Log assets $_{f,t-1}$	-0.072*** (0.014)		-0.072*** (0.014)		-0.073*** (0.014)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	13.58	72.63	174.39	1386.28	87.15	73.7
Observations	57,138	57,138	57,138	57,138	57,138	57,138
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 (24) and Section 4.4. The instrument variable for cs_{fnt}^r , bond-type specific exposure to natural disasters, follows the methodology of Ge (2022); and the instrument for dbr_{nt} is constructed from Equation (31). We winsorize $issuance_{f,t}(n)$, $cs_{f,t-1}^r(n)$, Tobin's Q, leverage, and debt coming due at 1st and 99th percentiles. Standard errors are clustered at the firm level.

E.6 Different dimensions of bond issuance

Table E.6: IV adding bond-type category FEs

Panel A: First stage test for flow-based instruments						
	$cs_{f,t-1}^r(n)$: Relative credit spread					
	(1)	(2)	(3)	(4)	(5)	(6)
$z_{t-1}^{cs}(n)$: Exogenous net flows	-0.048*** (0.007)	-0.055*** (0.008)	0.019*** (0.007)	-0.038*** (0.007)	-0.048*** (0.007)	-0.069*** (0.007)
$z_{t-1}^{dbr}(n)$	-0.050*** (0.014)	-0.142*** (0.015)	-0.031** (0.014)	-0.046*** (0.015)	-0.069*** (0.014)	-0.058*** (0.015)
<i>Tobin's Q</i> $_{f,t-1}$	0.001 (0.011)	0.022** (0.010)	0.002 (0.010)	-0.0003 (0.010)	0.002 (0.010)	-0.003 (0.010)
<i>Leverage</i> $_{f,t-1}$	0.002 (0.008)	-0.010 (0.007)	0.009 (0.007)	0.005 (0.008)	0.004 (0.008)	-0.001 (0.007)
<i>Debt coming due</i> $_{f,t-1}$	-0.037 (0.044)	-0.004 (0.041)	-0.020 (0.041)	-0.032 (0.044)	-0.032 (0.044)	-0.051 (0.043)
<i>Average CDS</i> $_{f,t-1}$	-0.057 (0.063)	0.106* (0.060)	-0.087 (0.057)	-0.050 (0.062)	-0.093 (0.062)	-0.088 (0.061)
<i>Log assets</i> $_{f,t-1}$	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)

Panel B: Second stage for relative credit spreads and demand-based risks						
	$issuance_{f,t}(n)$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r(n)$: Relative credit spread	-2.085*** (0.695)	-2.700*** (0.616)	10.010** (4.010)	0.943* (0.515)	-2.070*** (0.512)	-0.570* (0.305)
$dbr_{t-1}(n)$: Demand-based risk	-0.593*** (0.189)	-1.189*** (0.241)	1.501*** (0.475)	-1.169*** (0.146)	-0.624*** (0.155)	-0.636*** (0.114)
<i>Tobin's Q</i> $_{f,t-1}$	0.079 (0.058)	0.118** (0.047)	0.008 (0.104)	0.090** (0.037)	0.075* (0.042)	0.081** (0.036)
<i>Leverage</i> $_{f,t-1}$	-0.176*** (0.046)	-0.214*** (0.033)	-0.295*** (0.085)	-0.200*** (0.027)	-0.174*** (0.031)	-0.193*** (0.026)
<i>Debt coming due</i> $_{f,t-1}$	1.497*** (0.280)	1.598*** (0.188)	1.844*** (0.439)	1.600*** (0.155)	1.502*** (0.177)	1.555*** (0.152)
<i>Average CDS</i> $_{f,t-1}$	-0.693* (0.378)	-0.334 (0.282)	0.006 (0.695)	-0.326 (0.221)	-0.773*** (0.253)	-0.645*** (0.217)
<i>Log assets</i> $_{f,t-1}$	-0.071*** (0.011)	-0.073*** (0.008)	-0.054*** (0.019)	-0.075*** (0.006)	-0.073*** (0.007)	-0.069*** (0.006)

Firm FE	✓	✓	✓	✓	✓	✓
Bond-type Bucket × Quarter FE	Quarter	Rating	Maturity	Size	Cov-lite	Redemption
F-statistic	39.21	33.43	3.91	32.43	42.86	92.46
Observations	133,066	133,066	133,066	133,066	133,066	133,066

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-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 $t - 3$. Column (1) reports the baseline IV results corresponding to specification (5) in Table 6. Columns (2) through (6) sequentially introduce Bond-Type Bucket × Quarter fixed effects: Rating × Quarter FE, Time-to-Maturity × Quarter FE, Size × Quarter FE, Cov-Lite × Quarter FE, and Redemption Option × Quarter FE.

E.7 Issuance as a binary variable

Table E.7: IV using new issue dummy

	$\mathbb{1}[\text{new_bondtype}]_{f,t}(n)$					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs_{f,t-1}^r$: Relative credit spread	-0.502*** (0.143)	-0.425*** (0.119)			-0.575*** (0.174)	-0.559*** (0.172)
$dbr_{t-1}(n)$: Demand-based risk			0.030 (0.028)	0.023 (0.026)	-0.072 (0.046)	-0.121** (0.055)
Tobin's $Q_{f,t-1}$	0.001 (0.014)		0.001 (0.011)		0.002 (0.015)	
Leverage $_{f,t-1}$	-0.059*** (0.013)		-0.060*** (0.012)		-0.058*** (0.013)	
Debt coming due $_{f,t-1}$	0.393*** (0.071)		0.411*** (0.063)		0.391*** (0.074)	
Average CDS $_{f,t-1}$	-0.132 (0.098)		-0.106* (0.063)		-0.124 (0.106)	
Log assets $_{f,t-1}$	-0.014*** (0.003)		-0.013*** (0.003)		-0.014*** (0.003)	
Firm FE	✓		✓		✓	
Quarter FE	✓		✓		✓	
Firm × Quarter FE		✓		✓		✓
F-statistic	8.86	59.24	290.52	2509.96	39.21	32.32
Observations	133,066	133,066	133,066	133,066	133,066	133,066

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-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 $t - 3$. 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 independent variable $\mathbb{1}[\text{new_bondtype}]_{f,t}(n) = 1$ if the firm f has no outstanding for the bond type n in the past one year. The endogenous variables are constructed as described in Equation 24 and Section 4.4. $issuance_{f,t}(n)$, $cs_{f,t-1}^r(n)$, Tobin's Q, leverage, debt coming due are winsorized at 1st and 99th percentiles. Standard errors are clustered at the firm level.

F DBR and the cross-section of relative credit-spreads

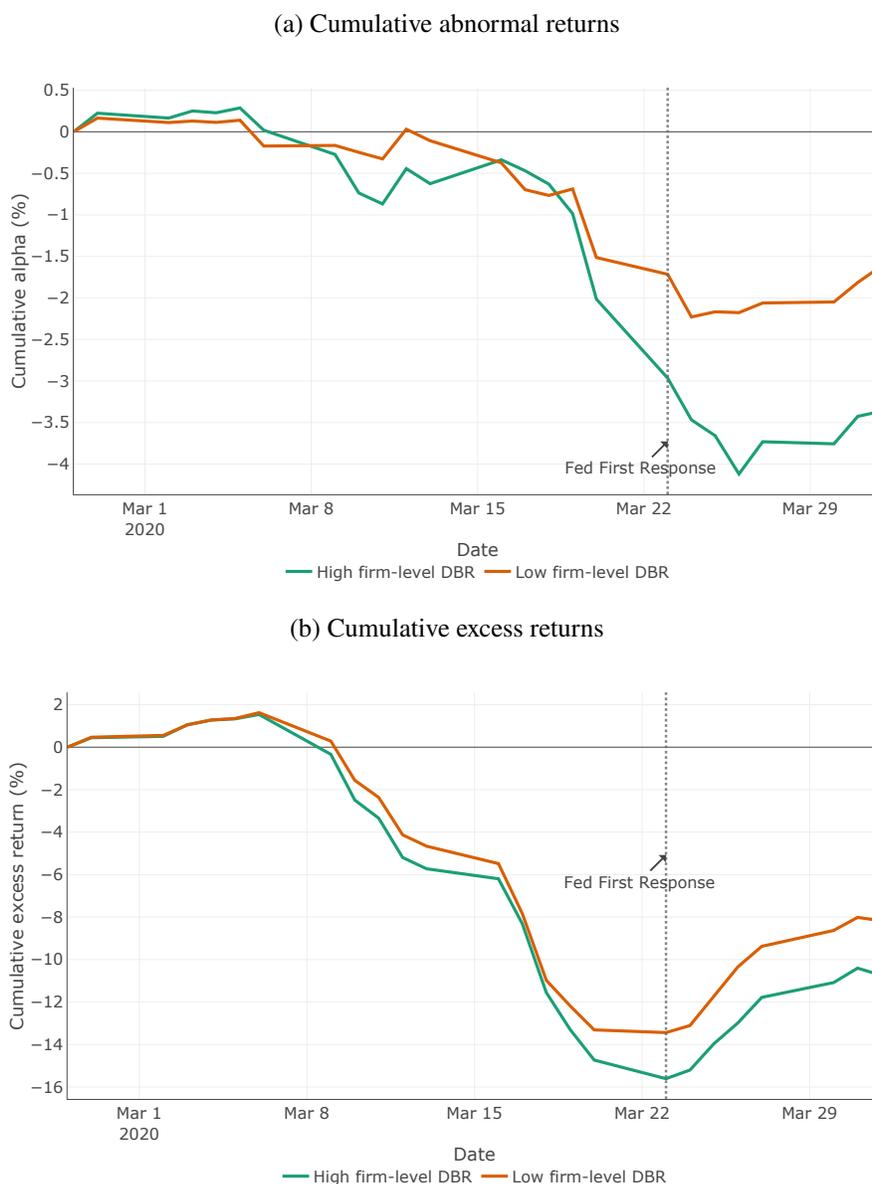
Table F.1: Relationship between demand-based risk and relative credit spread

	$cs_t^r(n)$: Relative credit spread				
	Panel regression				Fama-MacBeth
	(1)	(2)	(3)	(4)	(5)
$dbr_t(n)$	-0.00776*** (0.00290)	-0.00779*** (0.00268)	-0.00769* (0.00423)	-0.00613 (0.00432)	-0.00755* (0.00442)
$Duration_{t-1}(n)$			0.00548 (0.00637)	-0.00137 (0.00557)	0.00466 (0.00621)
$Average\ CDS_{t-1}(n)$			0.0207*** (0.00700)	0.0454*** (0.0103)	0.0217*** (0.00699)
Month FE		✓	✓		
Rating \times Month FE				✓	
Observations	9,319	9,319	9,319	9,319	9,319
R-squared	0.001	0.033	0.040	0.127	0.177

Note: This table shows the regression results of relative credit spreads on demand-based risk using an idiosyncratic 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. All independent variables are standardized (z-scored). The dependent variable, $cs_t^r(n)$, is winsorized at the 1st and 99th percentiles. Standard errors are clustered at the time level.

G Impact of demand-based risk in times of distress

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



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 firm-level demand-based risk portfolios split at the median. In Figure (b), portfolio excess returns are computed 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 issue more bond types. To examine this relationship, we regress the number of unique bond types issued in each firm-issuance event on the number of unique underwriters involved in that event, and include controls, firm and time fixed effects. Table H.1 shows the detailed regression 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.

Table H.1: Underwriter analysis

	# unique bond-types issued			
	num_bt			
	(1)	(2)	(3)	(4)
# unique underwriters	-0.032*** (0.005)	0.208*** (0.006)	0.217*** (0.006)	0.205*** (0.006)
Firm age		-0.003*** (0.001)	0.082*** (0.003)	0.136*** (0.052)
Tobin's Q		0.005 (0.005)	-0.009 (0.009)	-0.040*** (0.009)
Leverage		-0.095 (0.070)	-2.007*** (0.150)	-1.678*** (0.158)
Average CDS		0.002 (0.011)	-0.023* (0.013)	0.070*** (0.018)
Debt coming due		-10.132*** (1.182)	-3.033** (1.225)	-3.360*** (1.254)
Total assets (log)		0.388*** (0.007)	0.028 (0.038)	-0.016 (0.041)
Constant	2.104*** (0.015)	-3.370*** (0.106)		
Firm FE			✓	✓
Month FE				✓
Observations	23,026	23,026	23,026	23,026
R ²	0.002	0.182	0.378	0.398

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

Note: This table shows the effect of the number of unique underwriters hired by a firm for bond issuance on the diversification of its investor base. The sample is at the firm-issuance event level from January 2003 to December 2023. The dependent variable is the number of unique bond types issued on the event date, and the independent variable is the number of unique underwriters involved in the same event. The regression controls for firm characteristics, including age, Tobin's Q, leverage, average CDS spread, debt coming due, and total assets. All firm-level control variables are winsorized at the 1st and 99th percentiles.