Financially Sophisticated Firms

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Abstract

Using a newly comprehensive dataset that merges firm-level information with corporate bond issuance and holdings, we show that firms strategically use bond issuance not only to minimize their cost of capital but also to diversify their investor base. Investor specialization in certain bond characteristics allows firms to effectively shape their bondholder composition through issuance decisions. We find that firms with more diversified bondholder exhibit increased resilience to credit market shocks. Our analysis underscores the dual function of market timing in corporate bond issuance: it serves both to reduce capital costs and as a strategy for credit supply diversification. These findings emphasize the pivotal role of financially sophisticated firms in strategically issuing assets in a market increasingly reliant on non-bank intermediaries.

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

Our contribution is to show causal evidence of this dual role of market timing. We use an instrumental variable analysis to show that a one standard deviation reduction in credit spreads of a specific bond, driven by idiosyncratic investor demand shocks, leads to an increase in issuance equal to 3.4% of average monthly issuance. However, optimizing bond structure involves another crucial dimension: the management of *funding risk*, the firm's exposure to investor demand shocks that could affect its credit supply. We use a second instrument to show that firms are more likely to issue bonds with lower *demand-based risk* (DBR), our measure for how exposed an asset is to idiosyncratic investor shocks.[1] Diversifying funding risk is optimal because it leads to greater resilience to aggregate credit market shocks. As confirmation of the mechanism, we also show that this financially sophisticated behavior increases both shareholder and enterprise value.

Our findings bridge traditional asset pricing and corporate finance models by highlighting that asset supply is endogenous and capital supply is not perfectly elastic (Baker (2009)). The complexity of the corporate bond market allows corporate managers to cater to investor

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

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)). In fact, one of our additional results is that firms act more financially sophisticated in times when intermediaries are more constrained, thus adopting the role of financial intermediaries.

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

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

With the bond micro-data mapped to issuer firms and our defined bond types, we document four novel facts. First, a significant portion of firms in our sample demonstrates

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

financial sophistication: 60% of firms issue multiple bond types and 24% issue bonds through multiple subsidiaries as of 2023.

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

Third, we observe strong correlations between complex debt structures and firm funding risk and resilience. We compute a firm's funding risk as its exposure to investors' non-fundamental idiosyncratic shocks. Using investment flows into mutual funds and direct premiums into insurance companies, we estimate changes in investor demand that are likely to be orthogonal to bond fundamentals. Idiosyncratic flows gives us the basis for what we call *demand based risk*, i.e., the bond exposure to idiosyncratic demand shocks. Because investors differ in which bonds they hold, there is significant variation in a firm's exposure to demand based risk depending on which bonds they have outstanding. We find that firms with more bond types outstanding have lower funding risk. We interpret this as evidence that firms, by issuing various types of bonds, can match with a broader set of lenders, hence effectively diversifying investor's idiosyncratic shocks. We then connect a firm's funding risk to its resilience against credit market shocks, measured by its CDS beta relative to the aggregate CDX market. Our findings show that as a firm diversifies its investor base and reduces its funding risk, its credit market beta declines, indicating increased resilience. Specifically, within a firm, a one-standard deviation decrease in funding risk corresponds to a 5% reduction in its CDS beta relative to the mean.

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

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

First, we find that idiosyncratic wealth shocks affect prices. To construct idiosyncratic wealth shocks, we orthogonalize fund flows (for mutual funds) and direct premiums (for insurers) with contemporaneous returns, fund and time fixed effects. Our identification hypothesis is the residual flows causes variation in equilibrium credit spread, but are orthogonal to non-observable drivers of bond prices. To isolate variation in prices for a given bond type, we construct a relative credit spread metric that quantifies the divergence in credit spread among different bond types relative to other bond types in the market. We find that bond types that have more net inflows in a given period trade at relatively higher prices.

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 direct premiums. This instrument is unlikely to be correlated with the fundamentals of the market-wide portfolio of a particular bond type, yet 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 leads to an increase in issuance equal to 3.4% of average monthly issuance. Our results show that firms are price elastic in choosing bond capital structure.

Third, we show that financially sophisticated firms actively diversify their funding risk by issuing new bond types that have lower demand based risk. We construct a novel measure of an asset's *demand-based risk* (DBR) inspired by the model using the covariance in exogenous flows across the investors that hold the bond type, weighted by asset holding shares. We find that firms tend to issue new bond types with lower DBR, holding fixed prices. The magnitudes are also significant: a 1-standard deviation increase in DBR for a given bond type leads to a decrease in issuance equal to 1.1% of average monthly issuance. Thus, firms face a tradeoff when choosing what bonds to issue: they can minimize their cost of capital by selecting bond types that are temporarily trading at higher prices, or they can increase their resilience by issuing bond types that further diversify their funding risk.

Finally, we find support for our fourth hypothesis: firms create value by acting financially sophisticated, and do not increase their risks of financial distress. Using an event study analysis of two-day returns around issuance, we show that issuing more bond types with lower relative credit spreads increases both shareholder value and enterprise value, and does not significantly increase a firm's CDS (a common market-based measure of default risk). In magnitudes, issuing a relatively more expensive bond type has a net positive two-day abnormal return of 0.9 basis points. A trading strategy that times financially sophisticated issuance daily hence yields an abnormal annualized return of approximately 1.8%.

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

Our paper has important implications for understanding the role of corporates in financial markets that are increasingly relying on non-bank intermediaries. Much like banks, firms act as financial engineers, generating value for shareholders in the process. Indeed, we find that in periods when intermediary capital is low (per He et al. (2017)), firms are even more responsive to investor demands. As bank balance sheets shrink (Buchak et al. (2024)), borrowers structure securities directly to meet demands of institutional investors, taking on the role of intermediaries (e.g., DeMarzo (2005)). Moreover, our finding that investors buy more of bond types they previously held suggests that firms supply assets that are otherwise scarce to investors. Thus, firms are not merely using corporate bond markets to passively raise funds for investment; rather, they are actively helping investors risk share.

We consider complex debt structures to be the counterpart of the financial sophistication firms demonstrate in managing their assets, particularly with large firms maintaining large financial portfolios. Duchin et al. (2017) show that non-financial corporations hold complex asset portfolios comprising long-term treasury bonds, corporate bonds, and equity. In essence, what was traditionally labeled as "cash" extends far beyond mere liquid assets. Furthermore, Darmouni and Mota (2024) shows that precautionary motives alone fail to explain the composition of firms' financial portfolios, suggesting that additional motives drive their financial decisions, transcending core business operations. This paper illuminates how firms operate as advanced financial entities in their liability side as well, particularly in shaping their debt structures.

This paper contributes to the literature on how financial markets influence firm capital structure decisions. Firms are known to time the market by issuing equity when it is overpriced (Baker and Wurgler (2000), Baker and Wurgler (2002), Daniel and Titman (2006)), and similarly issue debt and buy back equity when debt is cheap (Ma (2019)). We show micro-level evidence that firms expand into different debt instruments to take advantage of price deviations arising from changes in investor demand, thereby building on work on aggregate corporate sector issuance (Greenwood et al. (2010)). Similar to Mota (2023), a firm's ability to "time the market" does not depend on asymmetric information between firm managers and investors, rather they firm respond to systematic demand shocks. Mota (2023) shows that firms' capital structure is affected by the demand for safe assets, in a similar vein, Kubitza (2023) shows that more demand from insurers increases firm issuance. Our study goes further, showing that debt structure can change in many other dimensions in response to investor demand.

Our results also build on a related literature where financial intermediaries cater to investors by engineering securities that feature characteristics demanded by investors (Gennaioli et al. (2010), Célérier and Vallée (2017), Lugo (2021), De Jong et al. (2013)), or by pooling and tranching assets (Allen and Gale (2004)), potentially to overcome informational frictions (DeMarzo (2005)). Directly related to our paper is Bisin et al. (2014), who provides a capital structure model with incomplete markets and hedging demand. We contribute to this literature by providing empirical evidence that firms are also capable of tranching their cash flows into different sets of securities to cater to heterogeneous investor demands.[3]

We also build on recent literature examining the effects of the rise in corporate bond markets. As firms rely less on banks and more on non-bank intermediaries (Buchak et al. (2024)), different sources of fragility can affect prices and the corporate sector (Goldstein et al. (2017), Darmouni et al. (2022), Ma et al. (2022), Falato et al. (2021), Jiang et al. (2022)). Insurers are known to act as asset insulators, as they are not forced to sell in times of crises (Chodorow-Reich et al. (2020), Coppola (2022)). We add to this literature in two ways. First, we show that there is value in diversifying investor composition in debt, since idiosyncratic shocks are not perfectly correlated across investors. Second, we show that firms

[3] A related strand of literature explores financial sophistication of households. For example, Calvet et al. (2009) construct a measure for household financial sophistication that incorporates underdiversification, risky share inertia, and a disposition effect.

can actively choose their investor composition by strategically selecting which bond types to issue. Hence diversifying credit supply is an important piece of the optimal capital structure decision. This builds on ideas by Friberg et al. (2024) that show that firms respond to stock price fragility, a measure of exposure to non-fundamental shifts in demands developed by Greenwood and Thesmar (2011). Moreover, we find that firm are motivated to create many different securities to meet heterogeneous investor demands, potentially speaking to the literature on the illiquidity of corporate bond markets (e.g., Bao et al. (2011), Goldstein and Hotchkiss (2020)).

There are many reasons investors can have heterogeneous demands for financial assets. For instance, the institutional differences and regulatory constraints across these non-bank intermediaries play significant roles in shaping lender preferences (Koijen and Yogo (2019),Vayanos and Vila (2021),Bretscher et al. (2022)). Insurance companies and mutual funds, which respectively hold 23% and 22% of corporate bonds, exhibit distinct preferences driven by regulatory and operational considerations. Insurance companies are constrained by credit ratings mandated by capital requirements, and must manage substantial exposure to long-term liabilities such as variable annuities (Becker and Ivashina (2015), Koijen and Yogo (2022), Sen (2023)). Property and casualty insurers respond to major operating losses from unusual weather events by reallocating their portfolios to safer securities (Ge and Weisbach (2021)). Mutual funds, on the other hand, face the challenge of managing short-term demandable liabilities, which are sensitive to returns and liquidity (Goldstein et al. (2017), Chen et al. (2010), Ben-David et al. (2022)), or may be governed by restrictive investment guidelines (e.g., Bretscher et al. (2023)). There could also be behavioral frictions that impact investor preferences for certain assets, and corporate managers react to persistent mispricing (Daniel et al. (2019)). We build on this literature by showing that firms, likely assisted by financial advisors like underwriters, respond proactively to these demand pressures by issuing higher-priced liabilities, thereby endogenizing the supply of assets in the market.

Next, we contribute to the optimal contracting literature on how firms select debt instruments. In choosing debt maturities, firms trade off between liquidity risk and private information about firm fundamentals (e.g., Diamond (1991), Diamond (1993)). In addition, debt maturity decisions can affect the extent of debt overhang (Myers (1977), Diamond and He (2014)) and a firm's strategic default timing (He and Milbradt (2016)), while decisions around collateral and covenants can affect investment incentives (Donaldson et al. (2019)). Related papers study how firms choose between bond markets and banks to manage the ease of ex-post debt renegotiation (Stulz and Johnson (1985), Bolton and Scharfstein (1996)), and how this decision interacts with real investment decisions (Morellec et al. (2015)). In this literature, the firm's desire to overcome agency frictions between investors and managers dictates the types of bonds that it issues, and typically, managers are price takers in securities markets. Our take is that investors demand heterogeneous cash-flows, influencing equilibrium prices and thus contributing to firm's bond structure choices. Also related are Choi et al. (2018) and Choi et al. (2021), which explore how firms smooth bond maturities given rollover risks; we build on these papers by exploring further sources of bond heterogeneity and observing that firms may diversify across investors as well as across time.

Finally, 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 debt outstanding. As the corporate bond market becomes an increasingly important source of capital for the U.S. economy, more papers have studied the interaction of the bond market with the real economy (e.g., Darmouni and Siani (2022)). Core to this exercise is the merging of bond data with firm data. Only by refining this merge can we

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

observe rich within-firm variation in bond types and investor holdings.

The rest of the paper is organized as following: Section 1 introduces the data and merge. Section 2 outlines how we categorize bonds into bond types, and documents empirical facts about investor composition and variation in bonds issued by the same parent company. Section 3 presents a theoretical framework and develops the testable hypotheses. Section 4 presents our empirical results, Section 5 presents additional tests, and Section 6 discusses implications. Section 7 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 issuers in FISD, and the match can change over time as companies merge, go through bankruptcy, or spin off subsidiaries. Moreover, the names of subsidiaries that issue bonds may look very different from the name of the ultimate publicly traded parent listed in Compustat. Finally, a parent company and its wholly-owned subsidiaries may all be separately listed in Compustat, so if we map the bonds to the subsidiary issuer but do not attribute them to the parent, we may miss parent-level capital structure decisions.

To address these complications, we begin by merging the two datasets with methods commonly used in the literature, and supplement with string matching and manual matching where needed. We verify our merge, described in detail in Appendix 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.[5]

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

Bond issuers are not representative of the entire corporate sector. The median bond issuer in our sample has $17.1 billion in total assets and $5.5 billion in total debt in 2023, while the median Compustat firm has $687 million in total assets and $97 million in total debt in 2023. Moreover, while the corporate bond market has grown in size significantly, the number of firms accessing bond markets has shrunk from around 1,800 in 2000 to just over 1,400 in 2023 (we show in Figure 1 the time series of both number of firms and the size of the bond market). Thus, in our analysis we will focus on only the subset of firms (that tend to be larger) that act financially sophisticated. Specifically, we consider only non-financial firms (i.e., those with NAICS3 codes other than 521, 522, or 523) with at least $1 million total assets and book value in the following analyses.

We utilize corporate portfolio holdings from CRSP and eMAXX. eMAXX holdings are used to calculate the share of bond k held by each individual investor, while CRSP holdings are employed to compute the portfolio-weighted fund flows into the bond each bond k held by the fund. Investors are then grouped into 6 categories: four categories of mutual funds

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

based on the majority of holdings, and two groups of insurers based on primary use. Our final eMAXX-based fund-bond-quarter level holdings dataset consists of 13,361 unique institutions and 41,892 corporate bonds from 2003 Q1 to 2023 Q4. Panel A of Table 1 presents the summary statistics of fund and bond characteristics for each investor category.

Some of our key measures and instruments are derived from fund flows. We obtain flows at the individual institution level: net inflows for mutual funds from CRSP, and direct premiums for insurers from NAIC. We truncate percentage flows at 100% to eliminate abnormal observations, and then isolate the exogenous component of net flows by regressing them on contemporaneous returns.[6] Before aggregating flows to the investor class-bond type level, we further truncate the orthogonalized flows at the 1st and 99th percentiles for each investor class per quarter to remove extreme outliers. Note that CRSP data only provides valid market values and shares held in portfolios starting in 2008, so all portfolio-weighted flow-based measures are limited to the period from 2008 Q1 to 2023 Q4.

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.[7]

[6]Detailed method is shown in Section 2.3

[7]Please refer to Figure C.1 in the Appendix for more details.

Exelon's behavior is not unique. Many firms issue bonds with multiple characteristics, resulting in a very large degree of heterogeneity in bonds. The bond complexity is, in part, a consequence of the firm's history, which includes consolidations, acquisitions, spin-offs, etc. However, even in the time of new issuance, firms tend to issue many bond types at the same time. In an attempt to quantify the heterogeneity of bond structure in a tractable way, we construct a measure of unique bond type based on five dimensions: credit rating, time to maturity, issuance size, covenants, and redemption option. Along the credit rating dimension, we split bonds into A-rated, BBB-rated, and high yield (lower than BBB- rating).[8] 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. Panel B of Table 1 presents the share of total amount outstanding held by different investor categories across the five dimensions of bond type characteristics. Table B.1 in the Appendix reports the distribution of the average number of bonds per period for all 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.

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

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 percent 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.[9] Firms with multiple bond types tend to be older, larger, better-rated firms that have more bonds as a share of overall debt (see Table 3 for summary statistics of firms with one versus multiple bond types). However, firms are comparable in overall leverage and profitability. Figure C.2 in the Appendix shows that as firms mature, the number of bond types increases. 23% of all firms in our dataset have over 5 bond types outstanding as of 2022. Importantly, firms exploit variation in all dimensions of the bond type classification. 53% of firms on average have bond types in multiple maturity buckets, 37% have bonds in multiple size buckets, 16% have bonds in multiple covenant-lite categories, 20% have bonds in multiple redemption categories, and 6% have bonds outstanding in multiple ratings buckets.

Moreover, 23% of firms in the sample issue out of multiple issuing entities as of 2021 - typically out of 2 unique entities in a given year. This behavior is more common in the utilities, transportation and financial industries- See Table C.1 in the Appendix for more information. While firms with multiple issuing entities tend to be larger, older, and more commonly investment grade, they are similar in average leverage and profitability to firms with only one issuing entity. An unsurprising but useful implication of this fact is that firms with more bond types also have wider dispersion in bond prices.[10]

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

[10] See Section B.1 in the Appendix for more discussion and empirical evidence.

2.2 Fact 2: Investors sort into different bond types

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

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

A striking picture emerges from this exercise, shown in Figure 4. Portfolios with high exposure to mutual funds holdings have -90% negative correlation with portfolios with high exposure to insures holdings. This strong negative correlation means that firms that are exposed to these two portfolios can diversify specific sector idiosyncratic shocks. By doing so, firms can minimize the cost of financial distress.

What might drive the negative correlation between mutual funds and insurer corporate bond portfolios? The literature has documented that because insurers have long-term liabilities, bonds in their portfolio are less likely to be sold in a downturn (Chodorow-Reich et al. (2020),O'Hara et al. (2022), Coppola (2021)). We show evidence that mutual funds can be "safe hands" too, in particular when insurers are forced to sell bonds upon the downgrading of a firm's credit rating. To show this, we run an event study analysis where we track the weighted average firm-level credit spreads in the months before and after the firm is downgraded from A to BBB. We compare firms that have a higher versus lower than median share of mutual fund holdings in the prior period. Figure 5 shows that firms with a higher share of mutual funds suffer a lower increase in credit spreads upon downgrade. This analysis shows that there are cases where mutual fund lenders may mitigate the magnitude of a negative shock. This suggests benefits to diversifying among mutual funds and insurers.

One implication of this mapping is that the more bond types a firm has outstanding, the more investors it has holding its bonds. Indeed, we show in Figure 6 that in the cross section, firms with more bond types outstanding tend to have more unique investors holding their bonds, controlling for total amount outstanding and time fixed effects.

2.3 Fact 3: Debt structure affects funding risk and resilience

Next, we show evidence that firms with more complex debt structures are more diversified across investors, and more diversified firms are also more resilient to negative shocks. To do this, we construct a firm-level measure of diversification across investor shocks, or "funding risk", in two steps: first, we compute a bond type-level measure of exposure to investor demand shocks, and then we aggregate it to the firm level based on what bonds the firm has outstanding.

We first define an asset's demand-based risk (DBR) as its exposure to idiosyncratic demand shocks, leveraging the stable investor base across bond types. Consider a case with N investors and K bond types. Let Ω be an $N \times N$ matrix that represents the variance-covariance matrix of investors' demand shocks. Let S_t be an $N \times K$ matrix, such that each line is the share of the outstanding bond k held by investor i. Bond DBR is represented as the variance-covariance matrix of the share-weighted idiosyncratic demand per bond:

$$\underbrace{DBR_t}_{K \times K} = S_t' \underbrace{\Omega}_{N \times N} S_t. \tag{1}$$

A firm's funding risk is then computed as its weighted exposure to DBR based on its outstanding bond types. We further normalize funding risk by total assets squared, so that funding risk does not simply scale with the size of the company, and take the square root.[11]

$$Funding\_Risk_{ft} = \sqrt{q_{ft}' \underbrace{DBR_t}_{K \times K} \underbrace{q_{ft}}_{K \times 1}}, \tag{2}$$

where $\boldsymbol{q}_{ft}$ is a $K \times 1$ vector of the par amount firm f has outstanding on bond k, normalized by its contemporaneous total assets.

To estimate funding risk in our data, we first aggregate exogenous net flows into different investor groups. We categorize investors into 6 groups: four groups of mutual funds based on the majority of holdings (long IG bonds, short IG bonds, long HY, and short HY), and

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

two groups of insurers based on primary purpose (life insurers and property and casualty insurers).[12] We then collect flows at the individual institution level for mutual funds using net inflows and insurers using direct premiums.[13] To extract the exogenous component of net flows, for each fund i in investor type I, we regress flows on contemporaneous returns, with fund fixed effects to absorb cross-sectional variation in fund characteristics, and quarter fixed effects to absorb market-wide shocks:

$$f_{it}^{I} = \beta \bar{R}_{it}^{I} + \alpha_i + \alpha_t + f_{it}^{I,\perp} \tag{3}$$

where $I \in$ Mutual Fund, Life Insurer, P&C Insurer. We residualize the net flows separately for each of the three investor types, such that the orthogonalized flows measure $f_{it}^{\perp}$ is mean zero and comparable. Table 4 shows the empirical Ω, the covariance of orthogonalized flows into each investor group. Life insurers have the lowest variance, while mutual funds that hold short securities have much more variance. Some off-diagonal terms are negative: e.g., the covariance between short IG mutual funds and long IG mutual funds, while other covariances are positive, such as between P&C insurers and short mutual funds. We then aggregate these orthogonalized flows to firm-level funding risk using asset holding shares and the amount of bonds that firms have outstanding per Equations (1) and (2).

We first establish that when firms have more bond types outstanding, funding risk is lower. See Figure 7 for a binned scatter plot of the firm's funding risk on the number of bond types outstanding, including firm fixed effects. As firms increase the number of bond types outstanding, their funding risk declines. This is consistent with the idea that having more different bond types allows firms to access a wider pool of investors and thus reduces

[12] 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 HY funds. Short funds are those where the maximum holdings share in bonds with time to maturity of less then 10 years is 95% or more across time, otherwise, they are classified as long funds.

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

their exposure to any one investor's idiosyncratic shocks.

Next, we test if access to a wider variety of institutional investors allows firms to better maintain access to capital in times of distress. To this end, we compute a time-varying measure of each firm's resilience by estimating forward-looking betas of a firm's CDS to the CDX index.[14] We interpret the estimated beta coefficient $\hat{\beta}_{f,t,t+5}$ as a measure of resilience: it is the firm's exposure to systematic risk in credit markets. The higher a firm's β, the lower the resilience. We then regress these estimated betas on normalized funding risk:

$$\begin{aligned} \beta^{CDS}_{f,t\to t+s} &= \gamma Funding\_Risk_{ft} + \delta_1 TobinsQ_{ft} + \delta_2 Leverage_{ft} + \delta_3 avgCDS_{ft} \\ &\quad + \delta_4 DebtDue_{ft} + \delta_5 \#BondTypes_{ft} + \alpha_t + \alpha_{rtg} + \varepsilon_{ft} \end{aligned} \tag{6}$$

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

Table 6 reports the results. We find funding risk across a firm's bond portfolio corresponds to higher beta to the market CDS in the next five year period. The coefficient on funding risk is positive and statistically significant. We interpret this result as follows: firms with lower funding risk are less exposed to aggregate risks represented by the CDS index going forward. This correlation is economically significant: specification (6) (including firm controls and month and firm fixed effects) shows that a one standard deviation decrease in funding risk decreases the beta by 0.02, which is 5% of the average beta.

[14] Specifically, we begin at the subsidiary level and compute the issuer-level CDS using the covariance of the issuer CDS and CDX index for the next five years and the variance over the next year, where CDS is calculated from U.S. daily data. See Table 5 for a summary of this and other statistics used in the empirical analysis. Next, we aggregate to firm-month level CDS betas, weighting by the amount outstanding of each subsidiary's bonds from the prior period:

$$\hat{\beta}_{ft} = \sum_{m\in f} w_{mf,t-1}\hat{\beta}_{mft} \tag{4}$$

$$w_{mft} = \frac{amt\_out_{mft}}{amt\_out_{ft}}. \tag{5}$$

2.4 Putting the facts together: financially sophisticated firms

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

3 Model

In this section, we introduce a model that captures the bond issuance behavior of financially sophisticated firms. We postulate 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), firms play a crucial role in determining the supply of such assets, thereby influencing equilibrium prices. To emphasize the core innovation of this study, we simplify the model, abstracting from many aspects of corporate debt structure. When we apply the model to the data in the next section, we will address other factors influencing corporate bond issuance decisions and discuss how we account for potential omitted variables that could affect the results. Additionally, we assume that the drivers of investor heterogeneity are exogenous to our model and focus on how this heterogeneity impacts firm behavior.

3.1 Environment

Consider a two-period model with one representative firm and two risk-averse agents that face short-selling and borrowing constraints. Agents face heterogeneous idiosyncratic wealth shocks. The firm's project revenues are dependent on a random variable ϵ, which is normally distributed with mean μ and variance σ, and is realized in time $t = 1$. There is one risk-free saving technology in perfectly elastic supply. Risk-free interest rates are normalized to zero. Firms can issue bonds whose payments are contingent on specific projects. Aside from risk-free debt, the only other financial assets available are those issued by the firm.

The two agents are indexed by i, $i \in \{A, B\}$. Each agent's wealth in time $t = 1$, w'_i, is a function of his invested wealth w_i, his portfolio allocation towards the risk-free asset, and bonds 1 and 2 $(q_{i,f}, q_{i,1}, q_{i,2})$, and the agent's idiosyncratic exposure to the firm's shock which we parameterize by θ_i. Each agent's wealth is thus:

$$w'_i = q_f + q_{i,1}x_1 + q_{i,2}x_2 + w_i\theta_i\epsilon(s). \tag{7}$$

Agents have mean-variance indirect utility over wealth in period $t = 1$ with a risk aversion parameter γ. Agents face short-selling constraints and cannot borrow to invest; therefore, their portfolio weights must be non-negative and add up to one. Hence, they solve:

$$\begin{aligned} \max_{\{q_{i,f}, q_{i,1}, q_{i,2}\}} \quad & \mathbb{E}\left[w'_i\right] - \gamma\mathbb{V}\left[w'_i\right] \\ s.t. \quad & q_{i,f} + q_{i,1}p_1 + q_{i,2}p_2 = w_{i,0} \\ & q_{i,f}, q_{i,1}, q_{i,2} \geq 0 \end{aligned} \tag{8}$$

There is also a representative firm that takes bond prices and portfolio allocation as given and chooses a capital structure to maximize its value. Specifically, the firm chooses its portfolio of bonds to issue with face values q_f, q_1, q_2. Because we want to focus on the financial decisions of the firm, we assume that the aggregate business of the firm is risk-free. Specifically, the firm needs to raise $f > 0$ in debt to invest in two NPV positive projects whose outcomes depend on ϵ. Project 1 pays out $f + d$ if $\epsilon \geq c$ and 0 otherwise, while the Project 2 pays out $f + d$ if $\epsilon < c$ and 0 otherwise. Hence, the firm's payoff is always $f + d$. The firm faces a decision: it can issue bonds that are a claim on the collective projects, which will have a risk-free face value of 1. Or the firm can also issue risky bonds that are each a claim to only one of the projects $j \in 0\{1, 2\}$, that pay $x_j = 1$ if the respective project is successful, or 0 otherwise.

The firm chooses a capital structure to maximize expected value, but its decision is limited by how it affects the firm's funding risk. As is common in the corporate finance literature, we assume there are quadratic costs in raising external funds. The innovation in our setting is that we make the funding risk dependent on the risk coming from investors' idiosyncratic demand for bonds. In particular, we define funding risk as

$$FR = \boldsymbol{q}'\Sigma\boldsymbol{q}, \tag{9}$$

where $\boldsymbol{q}$ is a 2×1 vector with the face value amount issued of each bond. Σ is the variance-covariance matrix of share-weighted idiosyncratic wealth shocks. Note this is the model equivalent of Equation 2, monotonically transformed.[15] The idea is that even though the firm does not directly choose agents' portfolio allocation, it can adjust its funding risk by choosing which bonds to issue because it can infer the investor composition in each bond.

[15]We model funding risk in a reduced form for simplicity. The underlying reason for firms to account for funding risk 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.

In the context of our model, the idiosyncratic wealth-weighted risk of each asset is

$$\tilde{\epsilon}_1 \coloneqq (s_{A1}\mathbb{A} + s_{B1}\mathbb{B})\,\epsilon \quad \text{and} \quad \tilde{\epsilon}_2 \coloneqq (s_{A2}\mathbb{A} + s_{B2}\mathbb{B})\,\epsilon$$

where s_{ij} represents the shares that investor i holds of asset j, and $\mathbb{A}, \mathbb{B}$ are each agent's wealth-weighted exposure to the shock ϵ:

$$s_{ij} \coloneqq \frac{q_{ij}}{q_j} \text{ for } i \in \{A, B\} \text{ and } j \in \{1, 2\},$$
$$\mathbb{A} \coloneqq w_{0,A}\theta_A \quad \text{and} \quad \mathbb{B} \coloneqq w_{0,B}\theta_B$$

Hence, the demand-based risk, or DBR, can be written as the covariance matrix of these idiosyncratic wealth-weighted risks:

$$\Sigma = \begin{bmatrix} \mathrm{Var}(\tilde{\epsilon_1}) & \mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) \\ \mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) & \mathrm{Var}(\tilde{\epsilon_2}) \end{bmatrix} \tag{10}$$

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 idiosyncratic shocks of the investors that hold its issues. We can then write the problem of the firm as:

$$\begin{aligned} \max_{\{q_f, q_1, q_2\}} \; & \mathbb{E}\left[d + q_1(p_1 - x_1) + q_2(p_2 - x_2)\right] - \gamma_f \boldsymbol{q}'\Sigma\boldsymbol{q} \\ s.t. \quad & q_f + q_1 p_1 + q_2 p_2 \geq f \\ & q_1(p_1 - x_1) + q_2(p_2 - x_2) + d \geq 0 \; \forall s, \end{aligned} \tag{11}$$

where p_f is the price of the risk-free bond, which we normalize to 1; p_1 and p_2 are the prices of the risky bonds.

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

We also assume that prices are such that markets clear. The total quantity of each risky bond j has to equal the amount held across investors i:

$$q_j = \sum_i q_{i,j} \ \forall j \tag{12}$$

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

3.2 Solution

In this section, we report the equilibrium prices and quantities. All proofs are in Appendix D. Let us introduce some notation to facilitate the exposition of the results. Define

$$\phi^* := \phi\Big(\frac{c-\mu}{\sigma}\Big), \quad \sigma\phi^* := cov(x_1, \epsilon), \quad \pi := Pr(\epsilon < c), \quad \text{and} \quad \sigma_X^2 := \pi(1-\pi)$$

where $\phi(x)$ is the PDF of the standardized normal distribution and represents the probability density of ϵ at the threshold c, above which Project 1 (and thus asset 1) pays out, and below which Project 2 (and thus asset 2) pays out; $\sigma\phi^*$ represents the covariance of asset 1's payout with the firm's shock ϵ; π is the expected payout of asset 1; and σ_X^2 is the variance of each risky asset's payoff.

To build intuition, we solve for the case where markets are perfectly segmented. Specifically, we assume $\theta_A < 0$ and $\theta_B > 0$, thus agent A has a hedging motive to buy only asset 1, which is negatively correlated with its idiosyncratic wealth shock, and similarly, agent B only holds asset 2.

3.2.1 Quantities

From the agents' first order conditions, we can derive the demand curves for bonds as

$$q_{A1} = \frac{\pi - p_1}{2\gamma\sigma_X^2} - \frac{\sigma\phi^*\mathbb{A}}{\sigma_X^2}, \quad q_{A2} = 0 \tag{13}$$

$$q_{B1} = 0, \quad q_{B2} = \frac{1-\pi-p_1}{2\gamma\sigma_X^2} + \frac{\sigma\phi^*\mathbb{B}}{\sigma_X^2} \tag{14}$$

Note that as long as $p_1 \neq \pi$ and $p_2 \neq 1-\pi$, demand for bonds is downward sloping and depends on investors' risk aversion and the variance of the risky asset.

From the firm's first order conditions, we can derive firm supply curves for bonds as

$$q_1 = \frac{1}{2\text{Var}(\tilde{\epsilon_1})}\left(\frac{p_1 - \pi}{\gamma_f} - 2q_2\text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})\right) \tag{15}$$

$$q_2 = \frac{1}{2\text{Var}(\tilde{\epsilon_2})}\left(\frac{p_2 - (1-\pi)}{\gamma_f} - 2q_1\text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})\right) \tag{16}$$

Hence, as long as $p_1 \neq \pi$ and $p_2 \neq 1 - \pi$, firm's supply curve is upward sloping, as firms will issue more of the high priced bonds. The slope depends on how sensitive the firm is to the funding risk and riskiness stemming from the idiosyncratic wealth shock of the agent that holds each bond.

Using market clearing, we can then solve for optimal firm issuance quantities in equilibrium, which leads to

$$q_1^* = -\phi\frac{\sigma}{\sigma_X^2}\mathbb{A}\cdot\frac{\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{B}^2}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)} \tag{17}$$

$$q_2^* = \phi\frac{\sigma}{\sigma_X^2}\mathbb{B}\cdot\frac{\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{A}^2}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)} \tag{18}$$

Proofs are in Section D.3. Notice that in the case $\mathbb{A} < 0$ and $\mathbb{B} > 0$, firm issues both assets. Furthermore, as long as $\gamma_f > 0$, the firm chooses to diversify across bonds to reduce its funding risk. Decreasing funding risk is effectively diversifying across investors' idiosyncratic demand shocks.

3.2.2 Funding Risk

In Appendix D.4, we can then use the optimal quantities to solve for the equilibrium funding risk, which is

$$FR^* = \left(\gamma\phi^*\frac{\sigma^2(\mathbb{A}^2 - \mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\text{Var}(\tilde{\epsilon_1}) + \gamma_f\text{Var}(\tilde{\epsilon_2})}\right)^2 \tag{19}$$

We interpret $(\mathbb{A}^2 - \mathbb{B}^2)$ as the *distance in the hedging needs*. As long there is some imbalance across investors, i.e., $\mathbb{A}^2 \neq \mathbb{B}^2$, the funding risk is positive.

3.2.3 Prices

The investors' problem and market clearing thus yield the following equilibrium prices

$$p_1^* = \pi - 2\gamma\phi\sigma\mathbb{A}\frac{\gamma_f\sigma^2(\mathbb{A}^2 - \mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)} \tag{20}$$

$$p_2^* = (1-\pi) - 2\gamma\phi\sigma\mathbb{B}\frac{\gamma_f\sigma^2(\mathbb{A}^2 - \mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)} \tag{21}$$

Proofs are in Section D.3. Note that given the assumptions, $\mathbb{A} < 0$ and $\mathbb{B} > 0$. Suppose that parameters are such that $(\mathbb{A}^2 - \mathbb{B}^2) > 0$, thus asset 1 is scarce compared to the frictionless benchmark. Hence p_1 is higher than the asset's expected payoff π. The opposite is true for asset 2, and in equilibrium p_2 is lower than its expected payoff $1 - \pi$.

It is useful to substitute in the equilibrium funding risk and write prices as

$$p_1 = \pi - \frac{\text{Var}(\tilde{\epsilon_1}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})} \cdot 2\gamma_f\sigma(\mathbb{A} + \mathbb{B})\sqrt{FR^*} \tag{22}$$

$$p_2 = 1 - \pi - \frac{\text{Var}(\tilde{\epsilon_2}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})} \cdot 2\gamma_f\sigma(\mathbb{A} + \mathbb{B})\sqrt{FR^*} \tag{23}$$

The higher the hedging needs of agents (i.e., the higher $\sigma, |\mathbb{A}|, |\mathbb{B}|$ are), the more prices deviate from expected payoffs.

3.2.4 Value of firm financial sophistication

We can use the model to write down an expression for the value of firm sophistication as a function of primitives. The maximum value of the firm with optimal issuance is thus:

$$V = d + \gamma_f \left(\gamma \phi^* \frac{\sigma^2(\mathbb{A}^2 - \mathbb{B}^2)}{\gamma \sigma_X^2 + \gamma_f \text{Var}(\tilde{\epsilon_1}) + \gamma_f \text{Var}(\tilde{\epsilon_2})} \right)^2 \tag{24}$$

Proofs are in Section D.4. Risk-averse investors prefer portfolios with lower variance. An increase in the magnitude of the idiosyncratic shock will also increase an investor's hedging demand. This drives up the comparative price for the asset favored by the agent with greater sensitivity-weighted wealth. The firm may suffer a per-unit loss for one of the two assets but is nonetheless encouraged to issue both securities for hedging. This phenomenon is potentially value enhancing because it does not reduce the value of the firm to have two different securities, yet it increases risk sharing among investors.

The value to the firm of financial sophistication can be represented by the second term in Equation 24. Figure 8 shows this object varies with investor heterogeneity. In this illustrative example, we allow investor A to have varying exposures to the aggregate shock ($\theta_A \in [-1, 0]$), while fixing $\theta_B = 0.5$. We set the wealth of both agents to 1. The graph shows the firm value arising from financial sophistication in three different cases: high, intermediate, and low investor risk aversion. The value of financial sophistication increases as (1) investors become more heterogeneous, i.e. as the magnitude of $|\theta_A| - |\theta_B|$ increases, and (2) investors become more vulnerable to shocks, i.e. as the magnitude of $|\theta_A| + |\theta_B|$ increases. These effects are magnified with investor risk aversion. Thus, as investors' desire to hedge, the value that firms may capture by issuing securities that allow investors to hedge also increases.

3.3 Hypothesis development

The model yields several testable implications of how investor hedging demand relates to firm behavior. Specifically, we test four hypotheses derived from the model (see Appendix D.5 for the derivations):

Hypothesis 1: Investors hedging needs affect equilibrium prices. Our first hypothesis is that idiosyncratic shocks to wealth (W) or preferences (θ) that impact investor hedging needs ($\mathbb{A}$ and $\mathbb{B}$) affect equilibrium prices. Specifically, when the net demand for an asset increases, the price increases. We illustrate this using variation in agent A's demand and prices for bond 1 in the model:

$$\frac{\partial p_1^*}{\partial \mathbb{A}} = -2\gamma\phi^*\sigma\frac{\gamma_f\sigma^2}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)}\Big((\mathbb{A}^2 - \mathbb{B}^2) + \frac{2\mathbb{A}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)}\Big) \tag{25}$$

Suppose that, as before, $\mathbb{A} < 0$ and $(\mathbb{A}^2 - \mathbb{B}^2) > 0$. Then $\frac{\partial p_1^*}{\partial \mathbb{A}} < 0$ i.e. $\frac{\partial p_1^*}{\partial |\mathbb{A}|} > 0$, thus increases in the magnitude of agent A's wealth or exposure to the aggregate shock will increase the price of the asset it prefers.

Hypothesis 2: Prices affect bond supply. Conditional on demand risk, firms will issue more bond types that have higher prices. Again we use asset 1 as an example:

$$\frac{\partial q_1}{\partial p_1} = \frac{\gamma\sigma_X^2 + \gamma_f(\text{Var}(\tilde{\epsilon_2}) - \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}))}{2\gamma_f\gamma\sigma_X^2(\text{Var}(\tilde{\epsilon_1}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}))} > 0 \tag{26}$$

– which in our formulation is satisfied as long as $\theta_A < 0$, $|\mathbb{A}| > |\mathbb{B}|$.

Hypothesis 3: Funding risk affects bond supply. Conditional on prices, firms will issue more bonds that lower their demand-based risk.

$$\frac{\partial q_1}{\partial \text{Var}(\tilde{\epsilon_1})} = -\frac{1}{2\text{Var}(\tilde{\epsilon_1})^2}\Big(\frac{p_1 - \pi}{\gamma_f} + q_2\sqrt{\text{Var}(\tilde{\epsilon_1})} \cdot \sqrt{\text{Var}(\tilde{\epsilon_2})}\Big) \tag{27}$$

Note that if $p_1 - \pi \geq 0$, thus prices are at least their expected payoffs, then $\frac{\partial q_1}{\partial \mathrm{Var}(\tilde{\epsilon_1})} < 0$ and firms issue more of the bond 1 when its DBR is lower.

Hypothesis 4: Financial sophistication creates value. By issuing different bond types in response to variation in idiosyncratic demand shocks, firms create value. Specifically, we can compute the expected value of net proceeds in equilibrium, and show that they are positive as long as $\gamma_f > 0$. This will always be the case if firms dislike funding risk.

$$(p_1 - \pi)q_1 + (p_2 - (1-\pi))q_2 = 2\gamma_f \left(\gamma\phi \frac{\sigma^2(\mathbb{A}^2 - \mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f \mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f \mathrm{Var}(\tilde{\epsilon_2})} \right)^2 > 0 \text{ if } \gamma_f > 0 \quad (28)$$

4 Empirical Results

In this section, we outline the empirical results of testing the model predictions.

4.1 Investor shocks affect prices

In this section, we test if idiosyncratic investor demand shocks affect prices, controlling for funding risk. Concretely, to proxy for prices of bond types, we construct a firm-specific relative credit spread for bond type k across all issuers other than firm f. We exclude credit spreads on the firm's own bonds to better approximate the market-wide price of a given bond type.

$$cs^r_{fkt} = \left(\frac{\overline{cs}_{kt,-f} - \overline{cs}_{t,-f}}{\overline{cs}_{t,-f}} \right) - \frac{1}{12} \sum_{\tau=t-12}^{t-1} \left(\frac{\overline{cs}_{k\tau,-f} - \overline{cs}_{\tau,-f}}{\overline{cs}_{\tau,-f}} \right) \quad (29)$$

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

Next, we compute idiosyncratic investor demand shocks for each bond type by aggregating the orthogonalized flows introduced in Section 2 to the bond type level:

$$z^{cs}_{kt} = \frac{\sum_{i \in I_{kt}} \hat{f}^{\perp}_{it} \times holdings_{ik,t-1}}{mktcap_{k,t-1}} \tag{30}$$

where I_{kt} is the set of funds in investor type I that holds bond type k in period t, $holdings_{ik,t-1} = AUM_{i,t-1} \times w_{ik,t-1}$ represents the dollar holdings of investor i of bond type k, and $mktcap_{k,t-1} = \sum_{b \in k} P_{b,t-1} amt_{b,t-1}$ is the market capitalization across all bonds of bond type k in the previous period.[16] As mutual fund flows are monthly and insurer flows are quarterly, the last step is to combine and convert the instrument to bond type-month level $z^{cs}_{kt} = z^{cs}_{MF,kt} + \frac{z^{cs}_{INS,kt}}{3}$.

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

$$\begin{aligned} cs^r_{fk,t-1} = {} & \beta z^{cs}_{k,t-1} + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} \\ & + \delta_4 DebtDue_{f,t-1} + \delta_5 log(Assets)_{f,t-1} + \delta_6 dbr_{k,t-1} + \alpha_t + \alpha_f + \epsilon_{fkt} \end{aligned} \tag{31}$$

We present the results in Table 7, and find that positive shocks in exogenous net inflows to a given bond type k reduces a bond type's relative credit spread, even within firm-month.

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

The interpretation of specification in column (2) is: holding all else constant, a 1 standard deviation decrease in a given bond type's exogenous net flows leads to a 1.1 percentage point increase in firm's relative credit spread of that bond type. This translates into a 0.02% increase in credit spreads compared to the average credit spread of all other firms in that period. [17] This supports Hypothesis 1: idiosyncratic investor demand shocks affect prices.

4.2 Firms supply assets in response to investor demand shocks

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

While the results above show that exogenous flows into a bond type (z_{kt}^{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, time-invariant fund characteristics, and market-wide movements (see Equation 3). If, for example, certain investors had private knowledge that BBB-rated firms would face difficulties issuing long-duration debt and thus created outflows from funds holding many BBB-rated long bonds, this should already be reflected in the returns for those funds and thus would have been removed from the instrument. Thus, the remaining variation in the instrument reflects exogenous shocks to household wealth and insurer premiums that are very unlikely to be correlated with unobservable fundamentals that affect firm decisions to issue certain bond types.

[17] The average credit spread of all other firms per month is 2.1%.

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

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

where we condition on positive net issuance across all bond types K for the firm f in the specified period. Our outcome variable $issuance_{fkt}$ is defined as the percentage change in amount outstanding for a given bond type k issued by the firm f in period t, normalized by total assets of the firm in the previous period $issuance_{fkt} = \frac{amt_{fkt} - amt_{fk,t-1}}{assets_{f,t-1}} \times 100$.[18]

Columns (1) and (2) of Table 8 show the results. The first stage results in Panel (A) are also in Table 7, and show that the instrument is relevant, as more net inflows to a given bond type k should reduce its relative credit spread. The second stage estimates in Panel (B) are supportive of our predictions that firms issue more of a bond type when it has a lower relative credit spread in the previous period. The interpretation for specification (5) is the following: all else equal, a 1 standard deviation decrease in a given bond type's relative credit spread leads to a 0.06 percentage point increase in the firm's issuance to assets ratio for that bond type in that month.[19] This is economically significant and represents about a 3.4% increase in the average issuance size of a bond type k in a month (about \$28 million). We show the OLS results in Table E.1 for comparison, which are near zero or even slightly positive. This is consistent with an attenuating bias, potentially arising from unobserved firm demand for a given bond type coinciding with higher credit spreads.[20]

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

[19]From Table 5, one standard deviation of the relative credit spread cs^r_{fkt} is 0.14, the coefficient estimate is 0.42, so $0.42 \times 0.14 = 0.06$.

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

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

4.3 Firms supply assets to reduce demand-based risk

Next, we test if firms respond to variation in demand-based risk when choosing *new* bond types to issue, conditional on prices. To do this, we compute bond-type level *demand-based risk* (*dbr*) by extracting the diagonal elements in Equation (1):

$$\underbrace{dbr_{kt}}_{1\times 1} = \mathbb{1}_k' diag(\underbrace{S_t'\Omega S_t}_{DBR_t}) \tag{33}$$

where $\mathbb{1}_k$ is an $K \times 1$ vector of zeros and 1 at k-th position, S_t is an $N \times K$ matrix of asset holding shares, with each element representing the share of outstanding bond k held by investor n, and Ω is an $N \times N$ variance-covariance matrix of the full time series of orthogonalized flows between the six investor categories. The intuition behind the measure is as follows: if a bond type k is held entirely be investor categories that face significant variance in exogenous flows, then the asset faces greater demand-based risk.

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 will mechanically increase the share s for all k held by investor class I, thus increasing exposure to that investor class in a way that is plausibly unrelated to the underlying fundamentals of issuers of that bond type.

$$z^{dbr}_{kt} = \mathbb{1}'_k diag(z^{cs'}_t \Omega z^{cs}_t) \tag{34}$$

where $\mathbb{1}_k$ is a $K \times 1$ vector with all elements equal to 0, except for a 1 in the k-th position.[21]

We show in Panel A of Table 8 that the instrument is relevant for demand-based risk. As long as exogenous flows into investors that hold a given bond type are uncorrelated with the firm fundamentals affect issuance decisions, the instrument satisfies the exclusion restriction.

We then test whether firms are more likely to issue a new bond type based on variation in relative credit spreads and dbr. Specifically, we run an IV regression where the second stage is:

$$\begin{aligned} issuance_{fkt} = {} & \gamma_1 \hat{cs}^r_{fk,t-1} + \gamma_2 \hat{dbr}_{k,t-1} + \delta_1 TobinsQ_{f,t-1} + \delta_2 Leverage_{f,t-1} + \delta_3 avgCDS_{f,t-1} \\ & + \delta_4 DebtDue_{f,t-1} + \delta_5 log(Assets)_{f,t-1} + \alpha_t + \alpha_f + \nu_{fkt} \end{aligned} \tag{35}$$

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

Columns (3) and (4) of of Table 8 show the IV results instrumenting only dbr_{kt}, and columns (5) and (6) show the results instrumenting both cs^r_{fkt} and dbr_{kt}. The coefficient on dbr is negative and significant, indicating that firms are more likely to issue bond types with lower demand-based risk, conditional on instrumented prices. Similarly to the way firms diversify their suppliers of goods to insure against idiosyncratic shocks facing a single supplier, firms will also diversify their supplier of credit in corporate bonds markets to insure against idiosyncratic shocks. The interpretation of coefficient on dbr in specification (5) is: all else equal, a 1 standard deviation decrease in a given bond type's demand-based risk

[21] See detailed construction of the instrument in Appendix H.

leads to a 0.02 percentage point increase in the firm's issuance to assets ratio for that bond type in that month.[22] This is economically significant and represents about a 1.11% increase in the average issuance size of a bond type k in a month.

The heterogeneity in firm responses is consistent with the model mechanisms. Figure 9 shows the estimated coefficients for relative credit spreads and dbr, as described in Equation 35, across different rating groups. Higher-rated firms clearly respond more to variations in bond prices than lower-rated firms. Interestingly, despite being highly responsive to prices, A-rated firms do not react to dbr. We interpret this result as evidence that A-rated firms are unlikely to face difficulties in raising external finance, therefore do not benefit from funding risk diversification. Figure 10 repeats the analysis for funding risk categories. While we do not observe a strong pattern in price responsiveness, it is clear that firms with higher current funding risk are less likely to issue bonds with high dbr. This aligns with expectations, as firms with high funding risk are already significantly exposed to idiosyncratic investor risk and stand to benefit the most from diversifying their funding risk. In the Appendix, we repeat the analysis for size groups in Figure E.1 and financial constraint categories in Figure E.2.

Our measure of demand-based risk is at the asset level, as per the model. However, a mean-variance firm also considers how the demand-based risk of an asset interacts with its existing portfolio of bonds. To this end, in the Appendix we construct an alternative measure of the incremental riskiness of a given asset to test how it affects firm issuance decisions. We call this measure $\Delta FR_{fkt} := \mathbb{1}_k' \Sigma_t q_{ft}$, and it represents how asset k changes the overall funding risk of firm f in time t, taking into consideration both the dbr of asset k and also its covariance with the firm's outstanding bond portfolio.[23] The method and results are discussed in Appendix E.4, and we find similar results as using the dbr measure.

[22]One standard deviation of the relative credit spread dbr_{kt} is 0.0113, the coefficient estimate is 1.684, so $1.684 \times 0.0113 = 0.02$.

[23]Note that this expression is derived from taking the first derivative with respect to q of the funding risk defined in the model, Equation 9.

4.4 Empirical value of firm sophistication

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

$$r^e_{ft} = \beta_0 + \beta_1 \left(\sum_{k \in f} \mathbb{1}[issuance]_{kft} \times \mathbb{1}[cs_{fk,t-1} < \underbrace{\bar{cs}_{fk}}_{\text{12 months}}] \right) \tag{36}$$
$$+ \beta_2 \Delta CDS_{ft} + \beta_3 TobinsQ_{ft} + \beta_4 log(Assets)_{ft} + \epsilon_{ft}$$

where the abnormal return is computed from the day prior to issuance to the day after issuance minus the market return. We control for CDS, Tobin's Q, and issuance size normalized by prior period assets. We report results in the first two columns of Table 9. Column (2) shows that, conditional on firm fundamentals, issuing a bond type that is relatively more expensive has a positive impact on the two-day equity return. Netting out the constant term, which represent the effect on stock returns of issuing in general, this effect is 1.38 basis points for the two day window, indicating an approximate annualized abnormal return of 1.8%. This is economically significant but not huge. A similar analysis in columns (3) of Table 9 using the firm's overall enterprise value similarly shows a positive effect; thus the value-add is not simply a transfer from existing debt to equity holders.

We show further that this behavior does not significantly increase the firm's default risk by running a similar event study and replacing the abnormal equity return with the firm-level change in CDS spreads minus the CDX index.[24] Column (4) of Table 9 presents the results. The coefficient on the interaction term of issuance and the relative credit spread is not statistically different from zero. Thus, issuing bonds with a relative credit spread does not increase the default risk of the firm on average.

5 Additional tests

In this section, we provide further empirical evidence of the mechanisms underlying our results. First, we show evidence of the model assumption that firms uniquely hold the ability to issue certain financial securities with payoffs contingent on the state of the economy. Second, we show how variation in investor composition corresponds to greater price dispersion within firm and lower funding risk. Third, we explore the source of the increased market resilience.

5.1 Firms provide a unique hedging service

If investors consistently demonstrate hedging demand for a given bond type, they should absorb the extra supply of bonds issued by the firm. Our model is static and we do not directly observe the hedging demand. We instead proxy this hedging demand by the portfolio weights for each bond type k. Specifically, using bond type by quarter data, conditional on positive net issuance in that bond type, we regress changes in portfolio weight of a given bond type on issuance in that bond type, interacted with the previous portfolio weight that the bond type made up in the investor's portfolio:

$$\Delta\omega_{i,k,t} = \beta_1 issuance_{k,t} + \beta_2 \omega_{i,k,t-1} + \beta_3 issuance_{kt} \times \omega_{i,k,t-1} + \alpha_{i,t} + \epsilon_{i,k,t}, \quad (37)$$

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

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

Results are reported in Table 10. We find that β_3 is positive and statistically significant. That is, the greater the portfolio weight of a given bond type k within a fund i in the prior period, the more the fund purchases when there is new issuance of that bond. The result is robust to fund–quarter fixed effects, which absorb time-varying fund fundamentals, as well as bond type fixed effects. If investors had a pure diversification motive, then we would expect to see $\beta_3 < 0$; that is, the greater the portfolio weight of a bond type in the previous period, the less the fund acquires given new issuance. If, on the other hand, investors had a pure mandate over the portfolio weights of different bond types, we would expect to see $\beta_3 = 0$. Instead, we find that investors that previously held large shares of a given bond type k increased disproportionately their holdings of that bond type following issuance, suggesting their demand for that bond type is insatiable by other assets in the market.

5.2 More concentration in investors reduces price dispersion

For firms to exploit demand-driven price variation, there must be meaningful price dispersion within firm. One way for firms to generate more price dispersion is to issue multiple bond types.[25] By doing so, firms effectively diversify their suppliers of credit. We can test directly how the extent of diversifying the investor base affects price dispersion. To measure investor base diversification, we compute the equivalent of the Herfindahl-Hirschman index for each

[25]We show in Appendix B.1 that more bond types corresponds to more price dispersion.

firm-month based on the shares that each investor holds of the firm's total bond portfolio:

$$HHI_{ft} = \sum_{i \in ft} s_{ift}^2, \tag{38}$$

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

Next, we run a regression of the within-firm price dispersion on the HHI, where price dispersion $\sigma_{CS,ft}$ is the standard deviation of the firm's credit spreads with firm and quarter fixed effects, and plot a binned scatter plot of the residuals from this regression in Figure 11. As expected, when a firm's investor base is more concentrated (higher HHI), it has lower price dispersion. It is thus less able to exploit the price variation when issuing bonds. Funding risk is also positively correlated with investor concentration, as we show in the second panel of Figure 11. This is consistent with the idea that as firms diversify their investor base, their overall exposure to idiosyncratic shocks is lower.

5.3 Fewer new lenders in bad times

Why is diversifying credit supply valuable? We showed in Section 2 that investors face demand shocks that are not perfectly correlated. Firms would thus value diversifying across investors only if it is costly to borrow from new investors when they demand capital. If this is the case, then by borrowing from many investors in good times, firms can diversify across these idiosyncratic shocks and maintain credit access when facing a negative shock. In theory, given information asymmetries between firms and investors, investors learn from prices. When corporate bond prices are low, investors cannot fully infer if it is due to bad fundamentals or to a liquidity shock of intermediaries. Thus, intermediaries are more likely to buy bonds from firms that are already within their investment universe, especially in periods of distress (Zhu (2021), Barbosa and Ozdagli (2021)).

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

$$share\_new_{ft} = \beta_1 avgCDS_{f,t} + \beta_2 CDX_t + \beta_3 TobinsQ_{f,t-1} + \beta_4 \frac{issuance_{ft}}{asset_{f,t-1}} + \alpha_t + \alpha_f + \epsilon_{ft} \quad (39)$$

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 diversify their funding risk.

6 Implications

What do our results say about the role of corporate bond issuers in the capital markets? The finding that investors lean into newly issued bond types that they already hold shows that firms are uniquely positioned to supply those assets that meet investors' demands. In this section, we push this implication one step further, and argue that firms may be acting as financial intermediaries in supplying different assets. Finally, we discuss magnitudes of the effects.

6.1 Firms as financial intermediaries

Traditionally, we consider financial intermediaries the agents that separate cash flows into tranches or package them into securitized products (DeMarzo (2005), Allen and Gale (1997)). In this view, when investors demand certain assets, firms should be agnostic, allowing intermediaries to create structured products that meet this demand. However, our evidence points to firms as important actors in this role. Why would this be the case? We hypothesize that part of the mechanism behind this firm behavior arises from the constraints facing intermediaries.

We present evidence suggestive of this hypothesis. We test whether the propensity of firms to issue bonds to respond to hedging demand becomes more pronounced in periods when traditional financial intermediaries are more constrained. Table 12 shows the results of the same instrumental variable specification describe in Section 4.2, but across different time periods: those with low versus high intermediary capital ratios, using the measure from He et al. (2017). The coefficients that represent how much firms tend to respond to heterogeneous investor demand by issuing specific bond types (i.e., how financially sophisticated they are) are significantly higher in magnitude when intermediaries are more constrained (when their capital ratios are low) than when they are not constrained. This is suggestive that in times when financial intermediary behavior is more constrained, firms act with greater financial sophistication.

6.2 Magnitudes

How large is the response of firms to investor demand, quantitatively? We compute some general statistics to approximate an upper bound of the magnitude of this phenomenon. Of the bond issuances in our sample where the firm has multiple bond types to choose from, 73% of newly issued bonds have a lower credit spread at issuance relative to the weighted average credit spread across bond types in the previous month. This is significant, considering that newly issued bonds tend to face a competing force towards a higher credit spread relative to comparable bonds trading in secondary markets. (Cai et al. (2007), Siani (2022)). A simple back of the envelope calculation shows that in the median firm-month, the issuers of these bonds that selected into bond types with lower credit spreads saved 10% of their overall bond interest expense on new issuances.[26]

7 Conclusion

Our empirical findings show that firms respond to heterogeneous investor demands by supplying bond types with higher prices and actively diversifying their funding risk. We interpret this result as value-maximizing firms actively completing markets in settings with heterogeneous demand. While the literature typically posits a perfectly elastic supply of capital from investors at a predetermined price, thus allowing firms to optimize their capital structures by weighing the relative advantages of issuing bonds versus equity, we show evidence of an alternative view: that is, firms *meet* heterogeneous investor demand by issuing different bond types.

Because markets are segmented, when choosing which bonds to issue, firms effectively also choose their investor's base. Since investor's demand shocks affect equilibrium prices and firms' access to the bond market, it is optimal for firms to manage their funding risk while choosing a capital structure.

We present a model to illustrate the mechanism driving firms to financial sophistication. Risk averse investors face short-selling constraints and are unable to fully hedge their idiosyncratic exposures to aggregate shocks. Firms are able to create value by supplying

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

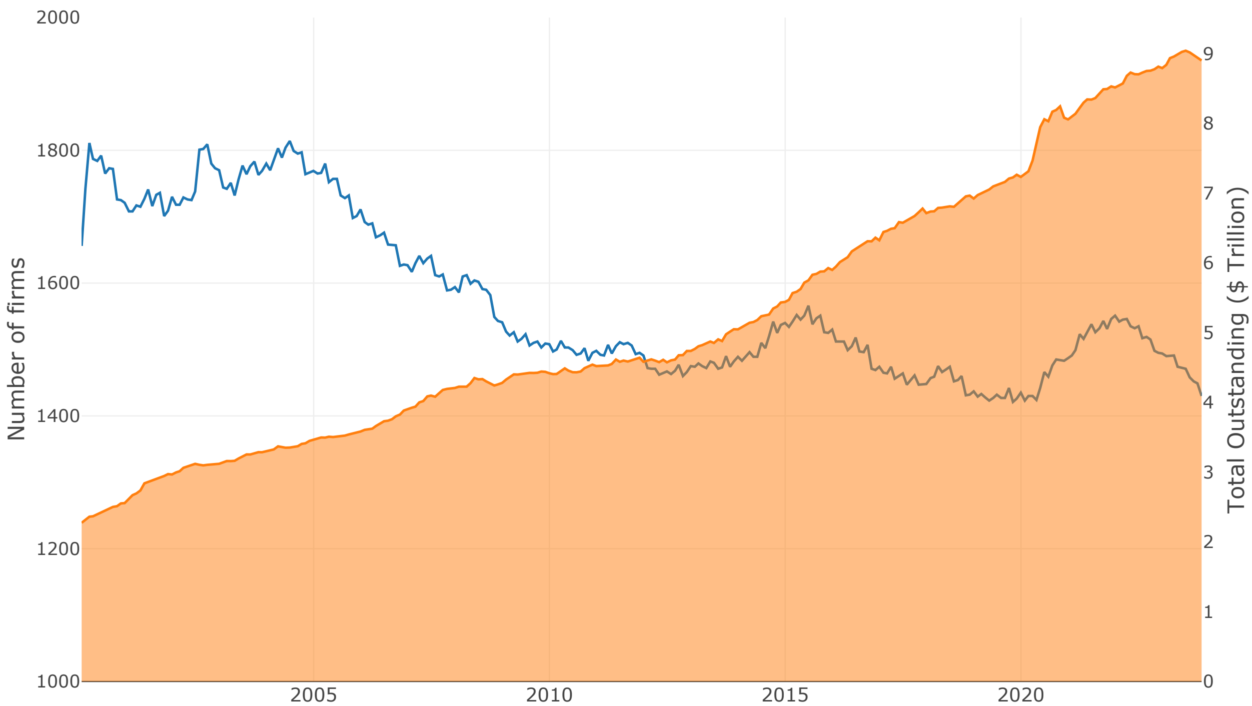
bonds that are backed by differing cash flows and can thus help investors hedge. We show evidence consistent with the key implications of the model.

Importantly, we show casual evidence of the dual role of market timing. Financially sophisticated firms actively minimize the cost capital by issuing bonds in high demand. By issuing many bond types, firms diversify their credit suppliers. Financial sophistication is value enhancing for the firm.

Why should firms undertake the potentially costly task of such financial sophistication? Our hypothesis is that in an economy populated by heterogeneous agents with unique cash-flow needs, firms play a vital role in customizing their bond issuances to cater to these specific demands. Because asset prices are intrinsically linked to investor demand, in taking this approach, firms not only fill a gap in the market but also strategically optimize their cost of capital. Our findings indicate that firms play an important role in financial markets by supplying assets that are demanded by investors and cannot be manufactured in other ways. Moreover, this financially sophisticated behavior increases firm value and makes firms more resilient to aggregate credit market shocks.

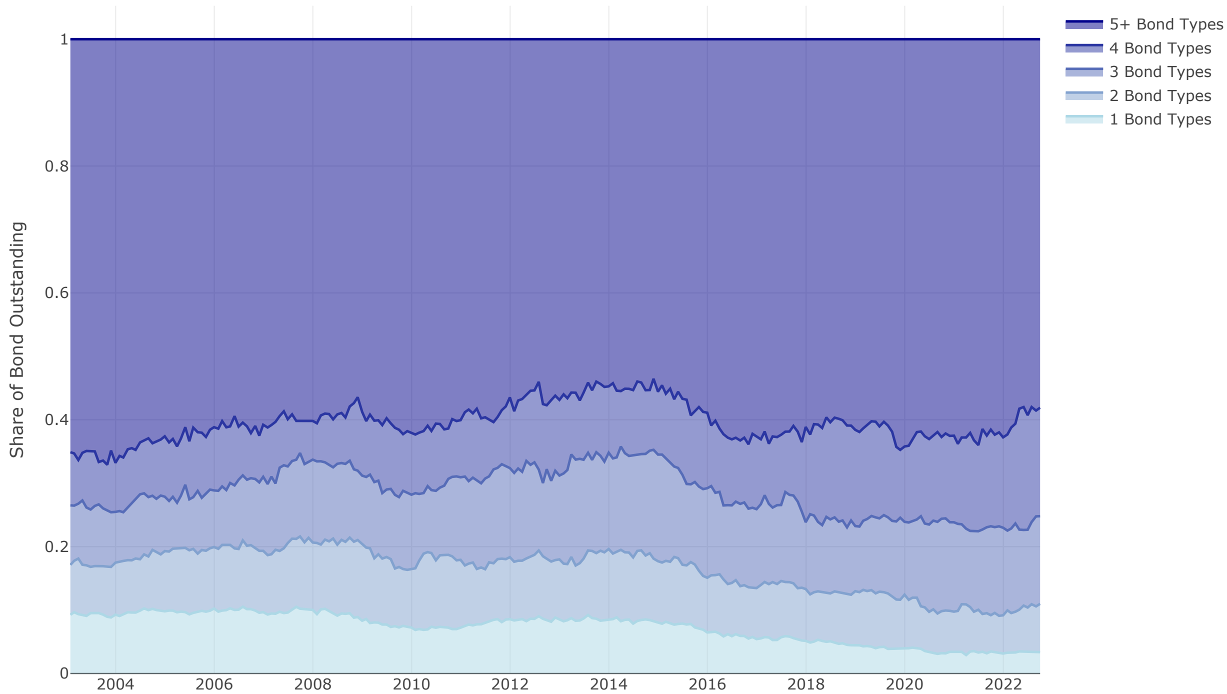
Figures

Figure 1: Bond Issuers and Corporate Bonds Outstanding



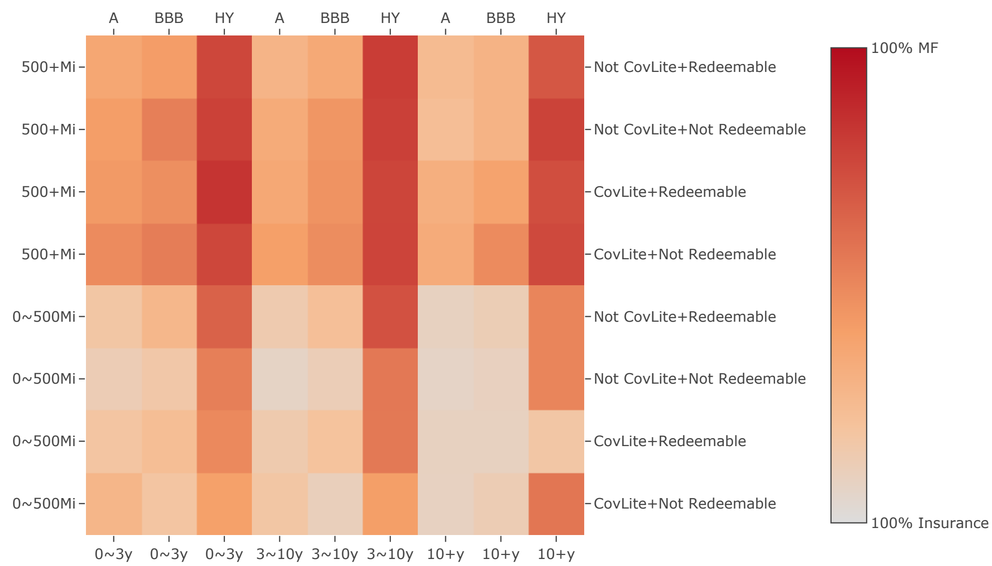
Note: This figure shows the number of U.S. firms with outstanding bonds and the total amount of outstanding corporate bonds over time. The line represents the number of unique firms (*gvkeys*), while the area chart reflects the total bonds outstanding in trillions of U.S. dollas. Data is monthly from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

Figure 2: One firm can issue many bond types



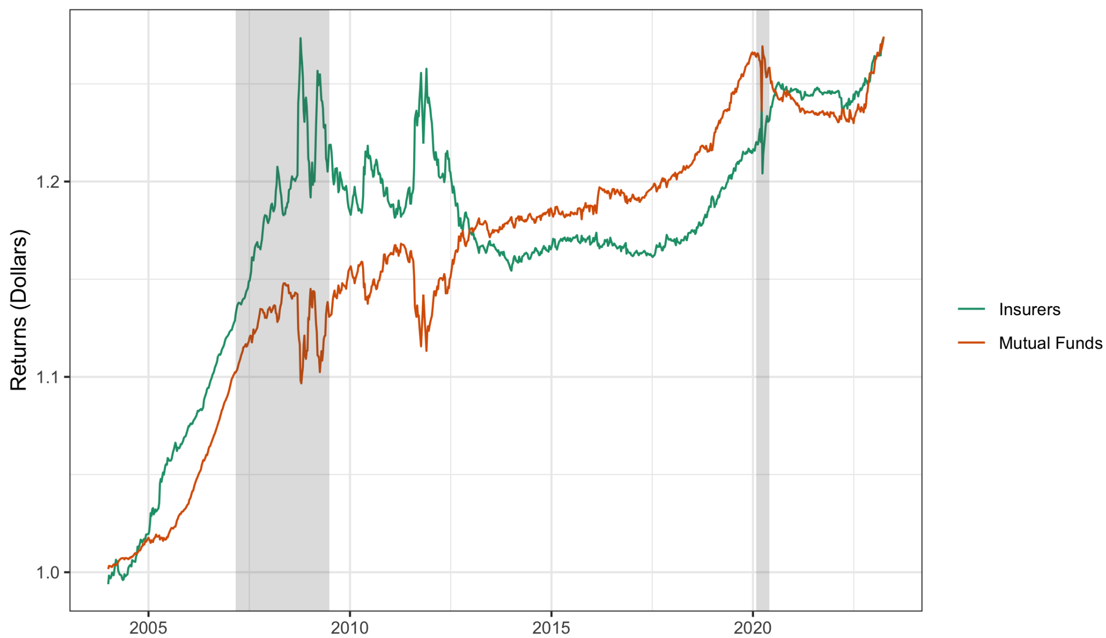
Note: This figure shows the distribution of firms by the number of bond types they issue over time. Bond type is define by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. Data is monthly from January 2003 to December 2023.

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



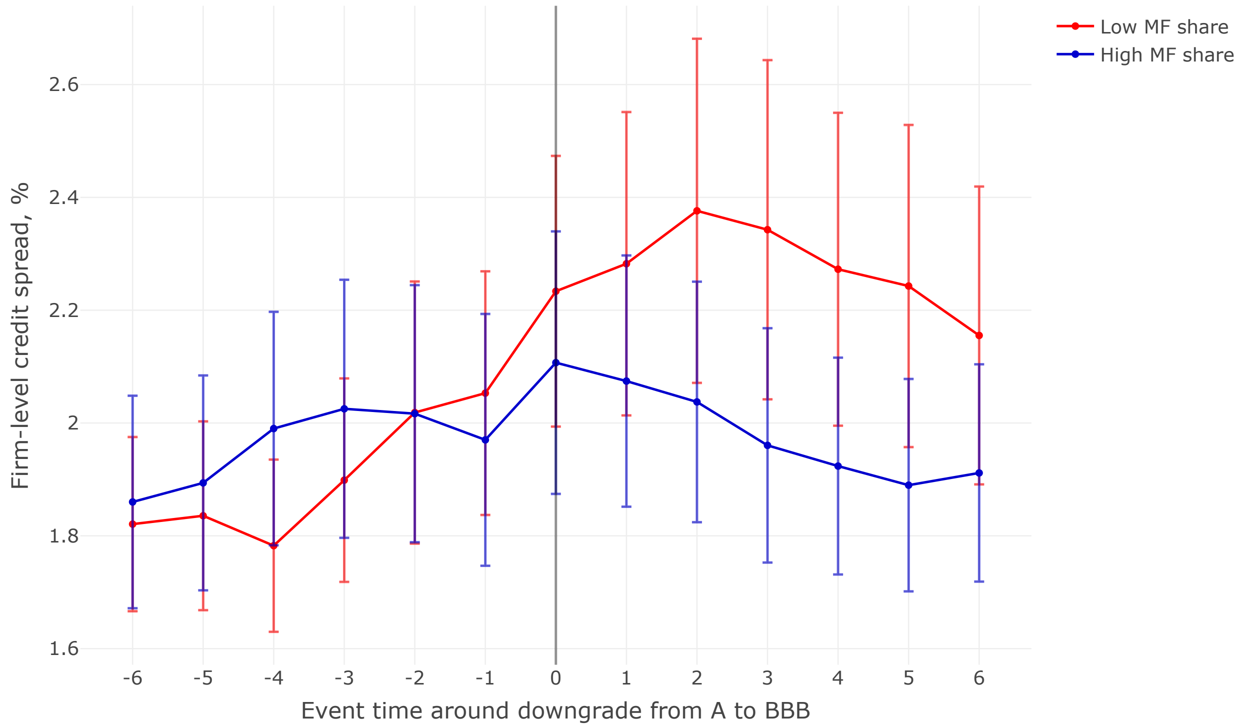
Note: This figure shows the share of amount outstanding held by mutual fund relative to the insurance companies holdings share in a given bond type. Bond type is define by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. We calculate the mutual holdings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

Figure 4: Long-Short Portfolio Returns



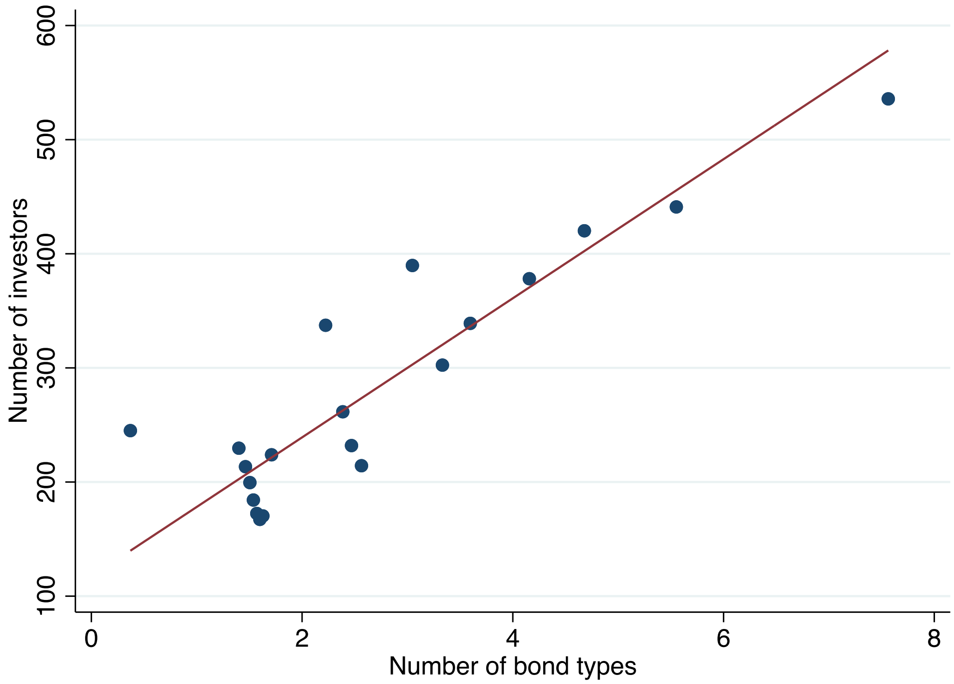
Note: This plot shows the cumulative return for two triple sorted long-short portfolios. The first long-short portfolio is long bonds that are held in high shares by insurers and short bonds that are held in low shares by insurers, within rating and maturity bucket. The second long-short portfolio long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

Figure 5: Firm Weighted Average Credit Spread around Downgrade from A to BBB



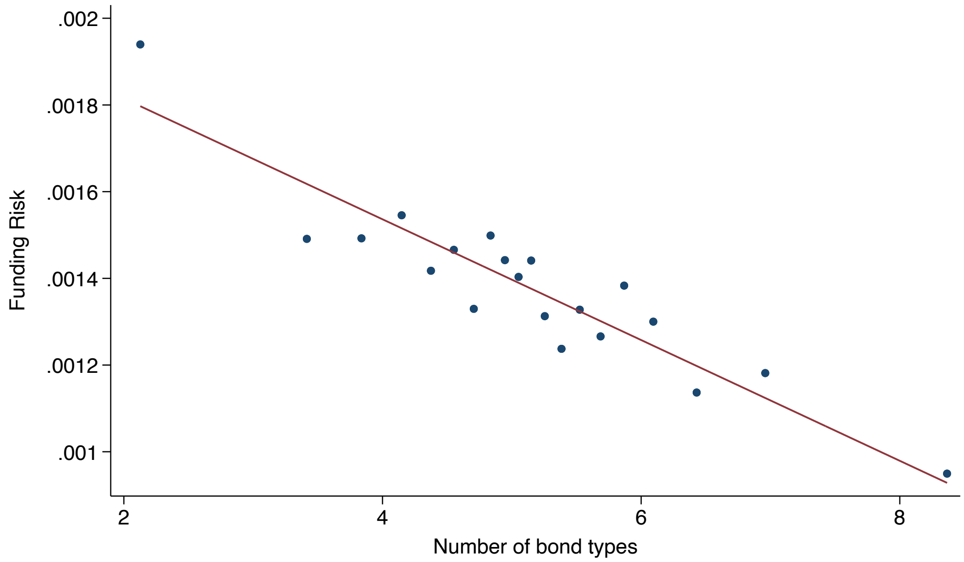
Note: This figure shows the firm-level credit spread for firms with low MF share and firms with high MF share, during the period six months before and after the credit rating downgrade event from A to BBB. Firm-level credit spread is the amount outstanding-weighted credit spread for all outstanding bonds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

Figure 6: Impact of Bond Type Variety on Investor Heterogeneity



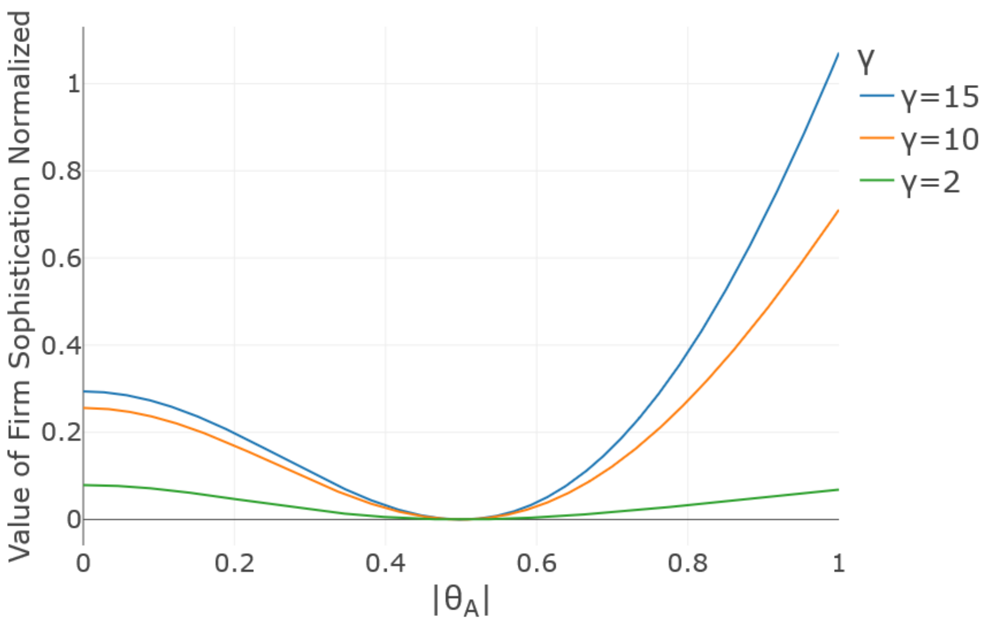
Note: This figure presents how the variety of bond types affect investor heterogeneity across a firm. The y-axis is the number of investors within a firm, while the x-axis is the number of bond types a firm issues. We control for firm's total amount of bonds outstanding and year fixed effects. Bond type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

Figure 7: Impact of Bond Type Variety on Funding Risk



Note: This figure presents how the variety of bond types affect the firm's funding risk. The y-axis is the funding risk computed from Equation (2), while the x-axis is the number of bond types within a firm. We control for firm-level characteristics including Tobin's Q, leverage, average CDS, and debt coming due. Firm fixed effect and month fixed effect are included. Bond type is defined by bond characteristics including rating, remaining maturity, size, covenants lite, and redemption. Data is quarterly from 2003 Q1 to 2023 Q4. We winsorize all the variables at 1% and 99% to remove outliers.

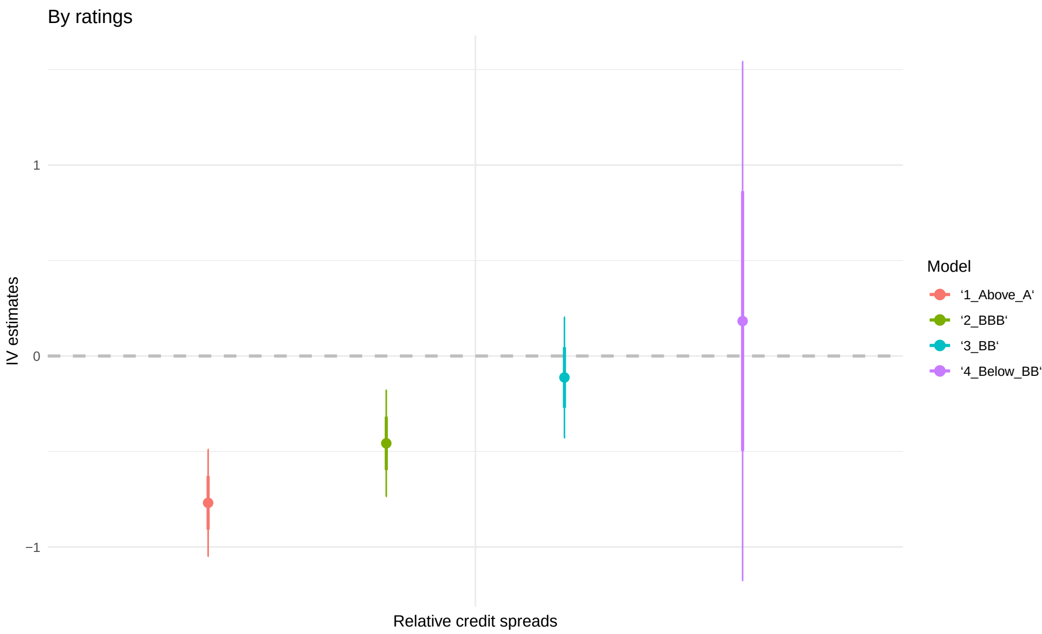
Figure 8: Value of firm sophistication



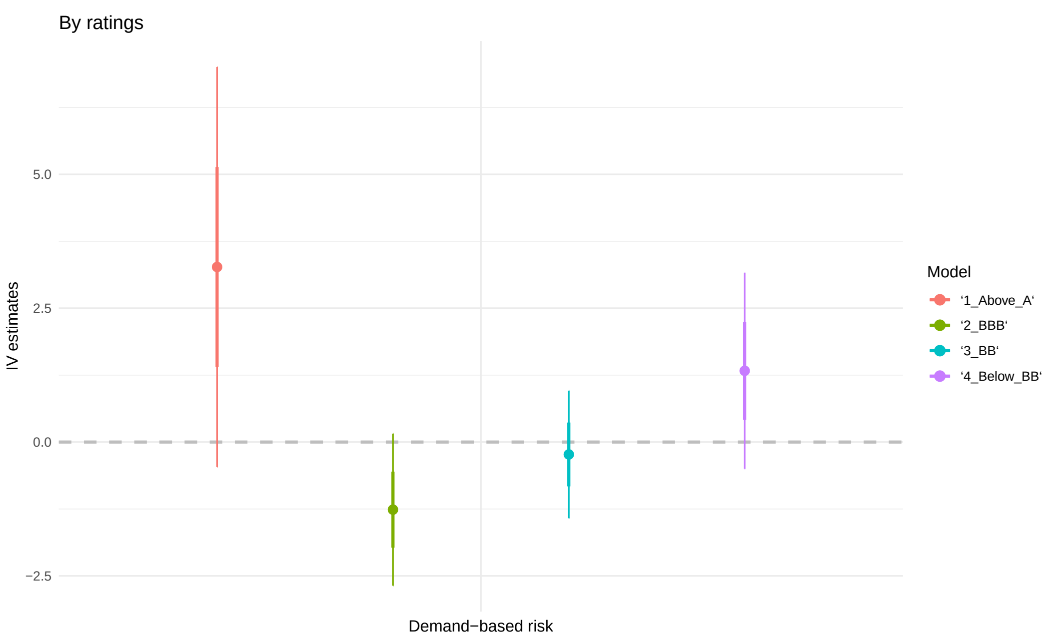
Note: This figure shows the value to the firm of financial sophistication as per the equilibrium expression Equation 24. Each line represents a different value for γ, the risk aversion of the investors. We set $\theta_B = 0.5$ and vary θ_A. Wealth for both agents is equal to 1, and we set the probability of each state $\pi = 0.5$.

Figure 9: IV heterogeneous effects: subsample by rating buckets

a. Second-stage estimates on relative credit spreads



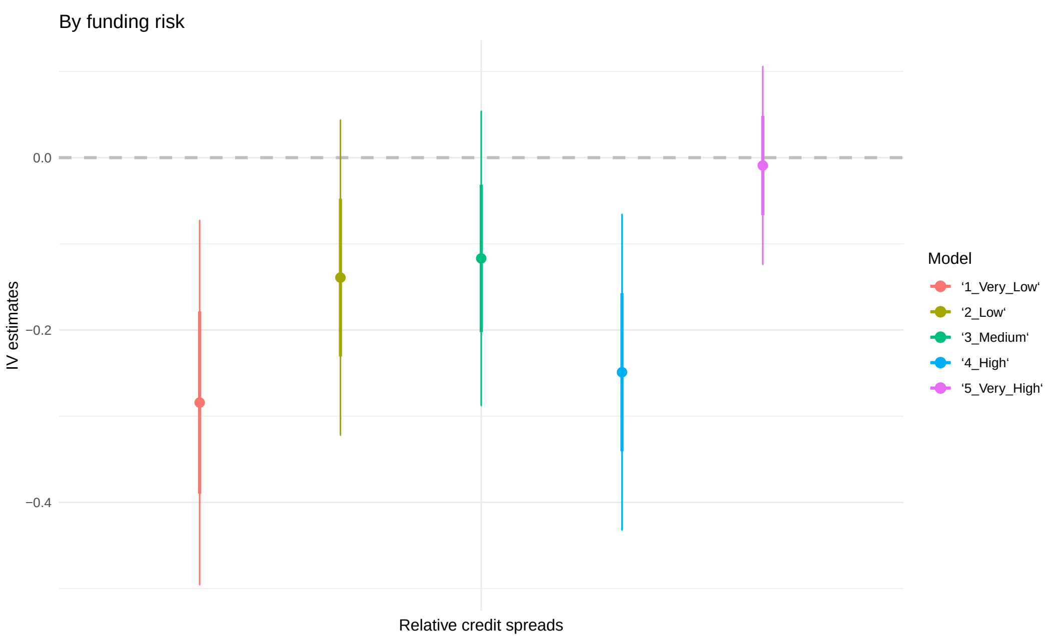
b. Second-stage estimates on demand-based risk



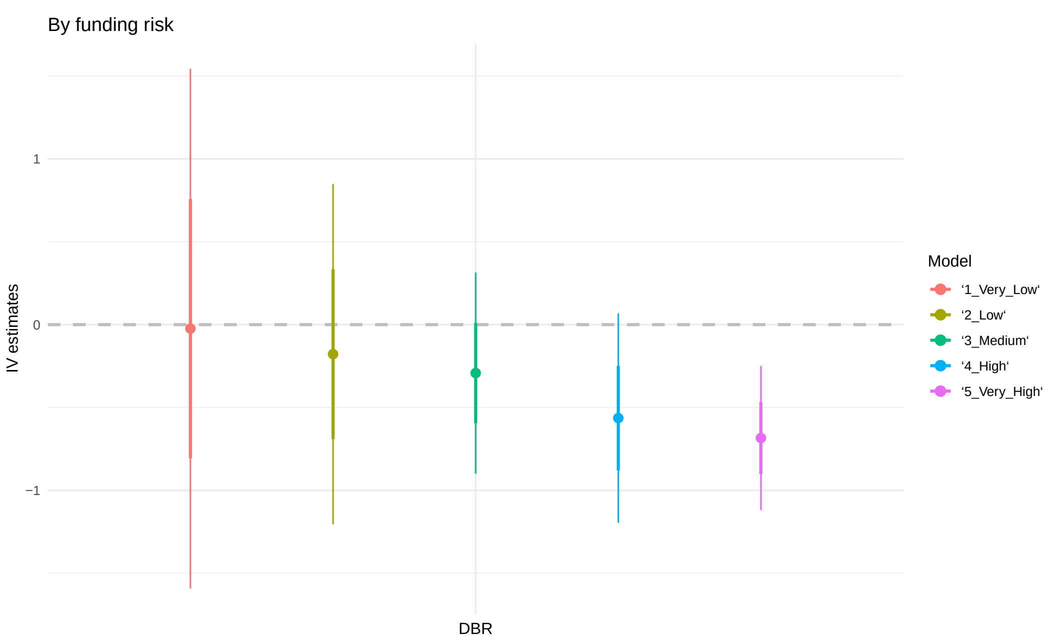
Note: This figure shows the IV heterogeneous effects, subsampling by firms' maximum ratings in the prior period. The endogenous variables are constructed from Equation (29) and (1). The instrument variables are constructed from Equation (30) and (34). We control for firm characteristics including Tobin's 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 monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

Figure 10: IV heterogeneous effects: subsample by funding risk

a. Second-stage estimates on relative credit spreads



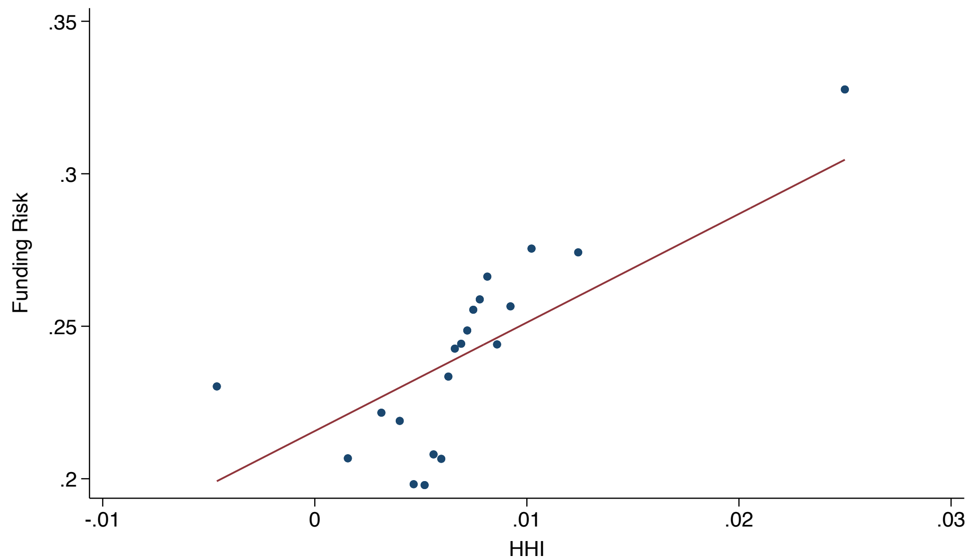
b. Second-stage estimates on demand-based risk



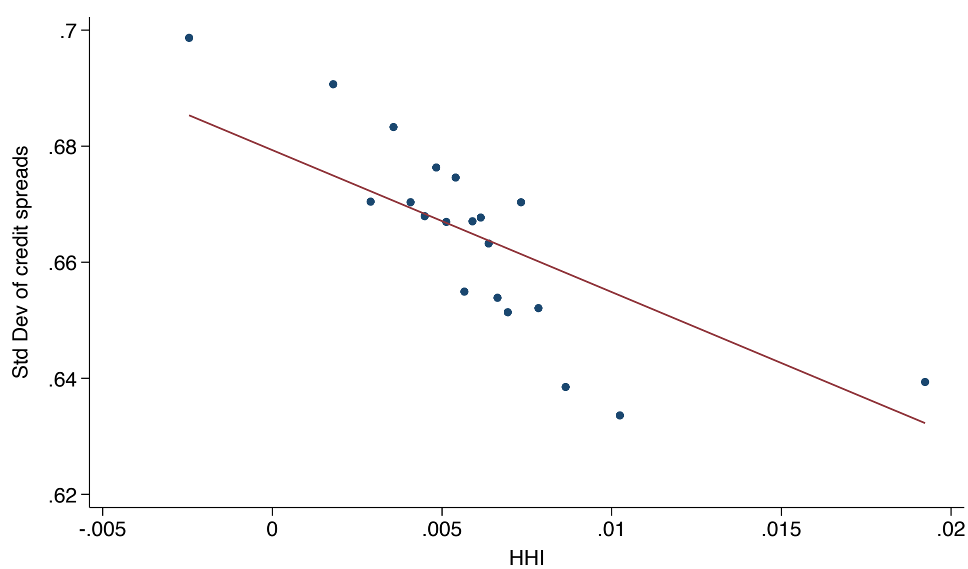
Note: This figure shows the IV heterogeneous effects, subsampling by firms' funding risk in the prior period. The endogenous variables are constructed from Equation (29) and (1). The instrument variables are constructed from Equation (30) and (34). We control for firm characteristics including Tobin's 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 monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

Figure 11: Impact of Bond Holding Concentration on Funding Risk

a. Relationship between HHI and Funding Risk



b. Relationship between HHI and Standard Deviation of Credit Spreads



Note: This figure shows the relationship between HHI and funding risk (Figure 1.a), and between HHI and standard deviation of credit spreads (Figure 1.b). We control for firm characteristics including Tobin's Q, leverage, average CDS, and debt coming due. Firm fixed effect and quarter fixed effect are included. Data is quarterly from 2003 Q1 to 2023 Q4. We winsorize all the variables at 1% and 99% to remove outliers.

Tables

Table 1: Summary statistics of investor categories

(a) Average fund and bond characteristics per investor category

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

(b) Distribution of investor holdings across each dimension of bond types

	Rating			Remaining Maturity			Size		Covlite		Redemption	
	A	BBB	HY	$<$ 3 years	3 to 10 years	$\geq$ 10 years	$<$ 500 million	$\geq$ 500 million	True	False	Yes	No
All Investors	46.61	33.68	19.71	24.84	50.34	24.81	27.67	72.33	24.31	75.69	76.25	23.75
IG/Long MFs	46.79	34.25	18.96	24.38	51.50	24.11	25.26	74.74	23.47	76.53	77.13	22.87
IG/Short MFs	54.35	34.42	11.23	37.30	60.52	2.17	16.90	83.10	27.70	72.30	71.52	28.48
Other/Long MFs	41.21	35.19	23.60	21.48	54.24	24.27	22.89	77.11	21.78	78.22	79.93	20.07
Other/Short MFs	17.29	25.87	56.84	22.42	73.95	3.63	23.39	76.61	20.17	79.83	86.36	13.64
PC Insurers	46.75	34.48	18.76	24.13	52.29	23.58	25.53	74.47	23.06	76.94	77.34	22.66
Life Insurers	46.73	34.51	18.76	23.85	50.89	25.25	27.24	72.76	23.44	76.56	77.13	22.87

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 the percentage of total amount outstanding held by different inventor categories across the five dimensions of bond characteristics. Investors holdings are calculated by dividing the total outstanding held by all investors that belong to a given category by the total bonds outstanding in a given bond characteristic category. Each cell represents the average holdings share across all periods in each investor category. Data is quarterly from 2003 Q1 to 2023 Q4. Data sources: FISD, eMAXX, CRSP, NAIC, and WRDS Bond Returns.

Table 2: Bond type description

(a) Bond types categorization

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

(b) Bond types consolidation

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

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

Table 3: Summary of firms by number of bond types

	Firms with 1 Bond Type			Firms with multiple Bond Types		
# Firms	1022			1536		
% A	4%			21.76%		
% BBB	14.25%			42.61%		
% HY	81.75%			35.63%		
Bond Characteristics						
	Mean	Median	Stdev	Mean	Median	Stdev
Credit Spread	6.4	5.33	4.42	2.24	1.58	2.42
Maturity	5.61	5.25	3.19	10.39	6.75	10.14
Outstanding(MI)	288.68	225	265.8	579.22	400	603.31
Firm Characteristics						
Age	17.38	15	12.31	30.53	29	15.93
Asset	5122.51	1332.24	31641.38	41392.65	9415.53	111308.79
Leverage	0.46	0.44	0.27	0.37	0.34	0.22
Profitability	0.02	0.02	0.02	0.02	0.02	0.02
Bonds/Debt	0.56	0.52	0.32	0.54	0.55	0.3
Bonds/Asset	0.26	0.2	0.23	0.19	0.16	0.15
# Investors	62.03	49	54.39	343	215	378.88
Funding Risk	0.59	0.21	2.64	0.36	0.19	0.85
Investors Holdings						
Mutual Funds	0.24	0.23	0.17	0.16	0.11	0.14
Insurance	0.15	0.06	0.2	0.33	0.32	0.21
Pension Funds	0.01	0	0.06	0.01	0	0.02
Others	0	0	0.01	0	0	0

Note: This table presents summary statistics of firms by number of bond types. Firms with 1 bond type refers to firms that consistently issue only one bond type throughout the whole time period. Conversely, firms with multiple bond types includes those issuing more than one bond types at any time point. We take average credit rating across all bonds within firm as a firm's credit rating within a quarter. % A is share of firms rated A or above; % BBB is share of firms rated BBB; % HY is share of firms rated BB or below. Firm age is defined as the number of years the firm has been listed on Compustat. Profitability is computed from operation profit, scaled by assets. Funding risk is defined as Equation (2). 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 and sourced from FISD, Compustat, and eMAXX.

Table 4: Covariance matrix of orthogonalized flows

invclass	IG/Long_MF	IG/Short_MF	Other/Long_MF	Other/Short_MF	Life_INS	PC_INS
IG/Long_MF	0.9316					
IG/Short_MF	-0.1490	1.5620				
Other/Long_MF	0.1472	-0.0596	0.2742			
Other/Short_MF	-0.4279	0.5134	0.2582	3.0490		
Life_INS	0.0764	-0.0483	-0.0115	-0.1259	0.0177	
PC_INS	-0.2512	0.2601	-0.0311	0.5858	-0.0656	0.6574

Note: This table shows the covariance matrix Ω within the Demand-Based Risk measures. We use the full time series of orthogonalized flows from 2008 Q1 to 2023 Q4 to calculate the covariance matrix. Investors are categorized into six groups: four groups of mutual funds based on majority of holdings (long IG bonds, short IG bonds, long HY, and short HY), and two groups of insurers based on primary purpose (life insurers and property and casualty insurers. Specifically, IG funds are defined as those where the maximum IG bonds holdings share is at least 95% overtime; otherwise, they are considered as Other funds. Short funds are defined as those in which maximum holdings share in bonds with time to maturity of less then 10 years is 95% or more across time; otherwise, they are considered as Long funds. Data is sourced from WRDS bond return, NAIC, and CRSP.

Table 5: Descriptive statistics of key variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Median	Pctl(75)	Max
Panel A: Unconditional full sample								
$issuance_{fkt}$	322,884	0.0357	0.2704	0.0000	0.0000	0.0000	0.0000	2.3773
$cs^{r}_{fk,t-1}$	322,884	0.0083	0.1403	−0.5209	−0.0477	0.0057	0.0618	0.5498
$z^{cs}_{k,t-1}$	322,884	−0.0003	0.0007	−0.0030	−0.0005	−0.0002	0.0001	0.0017
$dbr_{k,t-1}$	322,884	0.0136	0.0113	0.0019	0.0069	0.0107	0.0160	0.0812
$z^{dbr}_{k,t-1}$	322,884	0.0002	0.0005	0.0000	0.00001	0.0001	0.0002	0.0031
$Funding\_Risk_{f,t-1}$	322,817	0.2972	0.3708	0.0135	0.0998	0.1861	0.3319	2.4189
$Tobin's\ Q_{f,t-1}$	322,884	0.0398	0.0605	0.0045	0.0146	0.0227	0.0389	0.4609
$Leverage_{f,t-1}$	322,884	0.3273	0.1446	0.0284	0.2291	0.3262	0.4251	0.6861
$Average\ CDS_{f,t-1}$	322,884	0.0140	0.0155	0.0025	0.0057	0.0089	0.0150	0.0990
$Debt\ coming\ due_{f,t-1}$	322,884	0.0054	0.0105	0.0000	0.0000	0.0000	0.0069	0.0545
$Log(assets)_{f,t-1}$	322,884	10.3215	1.2533	7.5363	9.4547	10.2943	11.0989	13.5182
β^{CDS}	128,291	0.4725	0.5874	−1.0785	0.0973	0.3290	0.6332	12.8791
Panel B: Conditional on positive issuance								
$issuance_{fkt}$	6,750	1.7084	0.7998	0.0273	1.0208	2.2352	2.3773	2.3773
$cs^{r}_{fk,t-1}$	6,750	0.0103	0.1245	−0.4125	−0.0468	0.0084	0.0639	0.4870
$z^{cs}_{k,t-1}$	6,750	−0.0002	0.0007	−0.0030	−0.0005	−0.0002	0.0001	0.0017
$dbr_{k,t-1}$	6,750	0.0180	0.0170	0.0025	0.0090	0.0126	0.0202	0.0812
$z^{dbr}_{k,t-1}$	6,750	0.0002	0.0005	0.0000	0.00001	0.00004	0.0002	0.0030
$Funding\_Risk_{f,t-1}$	6,750	0.2857	0.3495	0.0135	0.0983	0.1858	0.3216	2.3010
$Tobin's\ Q_{f,t-1}$	6,750	0.0419	0.0645	0.0053	0.0150	0.0230	0.0413	0.4609
$Leverage_{f,t-1}$	6,750	0.3410	0.1493	0.0284	0.2421	0.3471	0.4347	0.6861
$Average\ CDS_{f,t-1}$	6,750	0.0135	0.0145	0.0025	0.0054	0.0085	0.0142	0.0848
$Debt\ coming\ due_{f,t-1}$	6,750	0.0074	0.0121	0.0000	0.0000	0.0000	0.0106	0.0545
$Log(assets)_{f,t-1}$	6,750	10.4829	1.2795	7.5416	9.5994	10.4711	11.3205	13.5182
β^{CDS}	2,820	0.4733	0.5707	−0.7980	0.1104	0.3331	0.6423	12.8791

Note: This table shows the descriptive statistics for key variables. Panel A shows the summary statistics across full sample of Table 8, and the Panel B is conditional on the positive net issuance firm-wide. $issuance_{fkt}$ is the amount issued for a given bond type k by firm f in period t, percentage normalized by the firm's total asset in the prior periods. ζ_{fkt} and instrumental variable κ_{kt} are constructed from Equation (29). Funding risk is calculated from Equation (2). $\beta^{CDS}_{f,t\to t+s}$ is a time-varying measure of firm's resilience from January 2008 to December 2018, which is constructed from Equation (4). The sample period is monthly from January 2008 to December 2023, considering the period of any positive outstanding for a given bond type k held by firm f. The sample includes non-financial firms conditional on positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. We winsorize all variables at 1% and 99% to remove outliers.

Table 6: Impact of firm's funding risk on credit betas

	$\beta^{CDS}_{f,t\to t+s}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Funding\ Risk_{ft}$	0.097***	0.064***	0.252***	0.053***	0.246***	0.062***
	(0.014)	(0.016)	(0.014)	(0.016)	(0.014)	(0.016)
$Tobin's\ Q_{ft}$			0.0001	−0.001	0.0003	−0.001
			(0.001)	(0.001)	(0.001)	(0.001)
$Leverage_{ft}$			0.380***	0.685***	0.351***	0.669***
			(0.026)	(0.045)	(0.026)	(0.045)
$Average\ CDS_{ft}$			0.167***	0.013***	0.167***	0.012***
			(0.005)	(0.004)	(0.005)	(0.004)
$Debt\ coming\ due_{ft}$			−0.918***	−0.074	−0.916***	−0.066
			(0.298)	(0.217)	(0.298)	(0.217)
$Log\ assets_{ft}$			0.138***	0.138***	0.131***	0.140***
			(0.003)	(0.010)	(0.003)	(0.010)
$Num\ unique\ bonds_{ft}$					0.001***	−0.001***
					(0.0002)	(0.0002)
Month FE	✓	✓	✓	✓	✓	✓
Firm FE		✓		✓		✓
Rating FE	✓		✓		✓	
Observations	33,534	33,534	33,534	33,534	33,534	33,534
R^2	0.120	0.628	0.218	0.634	0.218	0.635
Note:						*p<0.1; **p<0.05; ***p<0.01

Note: This table shows the estimates of how firm's funding risk would affect its resilience to negative shocks. The sample period is quarterly from November 2004 to December 2018. The independent variable is computed from Equation (2). The outcome variable is a time-varying measure of firm's resilience, which is constructed from Equation (4) and converted to quarterly data by taking the last records in each quarter. The firm-level controls include Tobin's Q, leverage, average CDS spread, debt coming due, log assets, and number of bond types in period t (start date of the five-year rolling window). We winsorize all variables at 1% and 99% to remove outliers. Data source: Markit CDS, Compustat, FISD, NAIC, CRSP, and eMAXX.

Table 7: Exogenous flows affect relative credit spreads

	$cs^r_{fk,t-1}$: Relative bond-type credit spread					
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{k,t-1}$: Exogenous net flows for MFs and Insurers	-15.226^{***}	-15.199^{***}	-18.760^{***}	-16.109^{***}	-16.084^{***}	-17.979^{***}
	(0.427)	(0.427)	(0.522)	(0.443)	(0.443)	(0.547)
$z^{dbr}_{k,t-1}$				-4.320^{***}	-4.327^{***}	3.000^{***}
				(0.578)	(0.578)	(0.631)
$Tobin's\ Q_{f,t-1}$		0.019^{***}			0.018^{***}	
		(0.006)			(0.006)	
$Leverage_{f,t-1}$		0.010^{**}			0.010^{**}	
		(0.004)			(0.004)	
$Debt\ coming\ due_{f,t-1}$		0.082^{***}			0.081^{***}	
		(0.025)			(0.025)	
$Average\ CDS_{f,t-1}$		0.335^{***}			0.334^{***}	
		(0.028)			(0.028)	
$Log\ assets_{f,t-1}$		0.001			0.001	
		(0.001)			(0.001)	
Firm FE	✓	✓		✓	✓	
Month FE	✓	✓		✓	✓	
Firm × Month FE			✓			✓
Observations	322,884	322,884	322,884	322,884	322,884	322,884
R^2	0.069	0.070	0.360	0.070	0.070	0.360

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

This table tests how exogenous flows affect firm's relative credit spreads. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The outcome variable and independent variable are constructed from Equation (29) and (30). We control for the instrument for demand-based risk for specifications (4) to (6). The firm-level characteristics in specifications (2) and (5) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Data source: FISD, Compustat, WRDS bond return, Markit CDS, eMAXX, and CRSP.

Table 8: How relative credit spreads and demand-based risks affect firms net issuance

Panel A: First stage test for flow-based instruments

	$cs^r_{fk,t-1}$		$dbr_{k,t-1}$		$cs^r_{fk,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{k,t-1}$	-15.199^{***}	-18.760^{***}			-16.084^{***}	-17.979^{***}
	(0.427)	(0.522)			(0.443)	(0.547)
$z^{dbr}_{k,t-1}$			3.445^{***}	3.400^{***}	-4.327^{***}	3.000^{***}
			(0.037)	(0.045)	(0.578)	(0.631)
$Tobin's\ Q_{f,t-1}$	0.019^{***}		0.001^{***}		0.018^{***}	
	(0.006)		(0.0004)		(0.006)	
$Leverage_{f,t-1}$	0.010^{**}		0.005^{***}		0.010^{**}	
	(0.004)		(0.0003)		(0.004)	
$Debt\ coming\ due_{f,t-1}$	0.082^{***}		-0.002		0.081^{***}	
	(0.025)		(0.002)		(0.025)	
$Average\ CDS_{f,t-1}$	0.335^{***}		0.007^{***}		0.334^{***}	
	(0.028)		(0.002)		(0.028)	
$Log\ assets_{f,t-1}$	0.001		0.0001^{*}		0.001	
	(0.001)		(0.0001)		(0.001)	

Panel B: Second stage for relative credit spreads and demand-based risks

	$issuance_{fkt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fk,t-1}$: Relative bond-type credit spread	-0.573^{***}	-0.477^{***}			-0.420^{***}	-0.340^{***}
	(0.079)	(0.074)			(0.077)	(0.088)
$dbr_{k,t-1}$: Relative demand-based risk			-1.839^{***}	-2.522^{***}	-1.684^{***}	-1.601^{**}
			(0.501)	(0.576)	(0.504)	(0.620)
$Tobin's\ Q_{f,t-1}$	0.058^{***}		0.050^{***}		0.057^{***}	
	(0.019)		(0.018)		(0.019)	
$Leverage_{f,t-1}$	-0.049^{***}		-0.045^{***}		-0.041^{***}	
	(0.014)		(0.014)		(0.014)	
$Debt\ coming\ due_{f,t-1}$	0.661^{***}		0.610^{***}		0.645^{***}	
	(0.082)		(0.078)		(0.080)	
$Average\ CDS_{f,t-1}$	0.140		-0.042		0.099	
	(0.093)		(0.078)		(0.087)	
$Log\ assets_{f,t-1}$	-0.016^{***}		-0.016^{***}		-0.016^{***}	
	(0.003)		(0.003)		(0.003)	
Firm FE	✓		✓		✓	
Month FE	✓		✓		✓	
Firm × Month FE		✓		✓		✓
F-statistic	96.69	360.7	745.4	137.65	407.93	243.36
Observations	322,884	322,884	322,884	322,884	322,884	322,884

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

This table shows how relative bond-type credit spreads in the previous period would affect the firm's issuance of bond type k in period t. The sample period is monthly from January 2008 to December 2023, considering the period of any positive outstanding for a given bond type k held by firm f. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The outcome variable is the amount issued for a given bond type k 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 (29) and (1). The instrument variables are constructed from Equation (30) and (34). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

Table 9: Impact of corporate bond issuance on firms return and CDS

	$r^e_{equity,ft}$		ΔCDS^e_{ft}	$r^e_{enterprise,ft}$
	(1)	(2)	(3)	(4)
$\sum_{k\in f} \mathbb{1}[issance]_{fkt} \times \mathbb{1}[cs_{fk,t-1} < \bar{cs}_{fk}]$		8.117**	0.119	5.166**
		(3.237)	(0.102)	(2.223)
$Log\ assets_{ft}$		2.047	0.023	1.851
		(1.736)	(0.053)	(1.192)
$Tobin's\ Q_{ft}$		3.731*	0.031	2.491*
		(1.951)	(0.059)	(1.340)
ΔCDS^e_{ft}		−9.994***		−7.073***
		(0.279)		(0.192)
$Average\ CS_{f,t-1}$			−0.140**	
			(0.063)	
Constant	0.616	−37.119	−0.190	−31.512*
	(1.606)	(25.821)	(0.819)	(17.735)
Controls		✓	✓	✓
Observations	13,386	13,386	13,750	13,386
R^2	0.000	0.088	0.001	0.093
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This table shows how the firm's increased issuance of a given bond type k in period t responding to the relative credit spread of that bond type k in the previous period would affect the firm's abnormal equity return and default risk in period t. The sample includes firms' new issues events from January 2003 to December 2023. The outcome variables are the firm's equity return relative to the market return in columns (1) and (2), the change in CDS spread relative to the CDX in column (3), and firm's weighted enterprise return relative to the market return in column (4), all in basis points, from period $t-1$ to $t+1$, where t is the event date of firm f issuing bond type k. $\mathbb{1}\{issuance\}_{kft}$ is a dummy variable for whether firm f issues a given bond type k in period t, and the independent variable is the sum of the products of former two components across all bond types issued by firm f in period t. The firm-wide controls include contemporaneous Tobin's Q, log assets, change in CDS relative to the CDX, and average credit spread in the previous period. We winsorize all the continuous variables at 1% and 99% to remove outliers.

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

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

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

Table 11: Impact of negative shocks on investor heterogeneity within a firm

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

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

Table 12: Subsample Intermediary Capital Ratio

Panel A: First stage test for flow-based instrument					
	$cs^r_{fk,t-1}$: Relative bond-type credit spread				
	Full sample	Interaction		Low ICR	High ICR
$z^{cs}_{k,t-1}$	-16.088^{***}	-12.957^{***}	-14.755^{***}	-16.415^{***}	-15.738^{***}
	(0.443)	(0.665)	(0.696)	(0.540)	(0.764)
$z^{dbr}_{k,t-1}$	-4.328^{***}	-4.243^{***}	-10.617^{***}	0.392	-10.635^{***}
	(0.578)	(0.578)	(0.929)	(0.714)	(0.951)
$z^{cs}_{k,t-1} \times \mathbb{1}[LowICR]_t$		-4.807^{***}	-2.182^{***}		
		(0.762)	(0.818)		
$z^{dbr}_{k,t-1} \times \mathbb{1}[LowICR]_t$			9.802^{***}		
			(1.119)		
Panel B: Second stage for relative bond-type price discount					
	$issuance_{fkt}$: Net issuance to assets ratio				
	Full sample	Interaction		Low ICR	High ICR
$cs^r_{fk,t-1}$: Relative bond-type credit spread	-0.420^{***}	0.015	-0.012	-0.613^{***}	-0.070
	(0.077)	(0.180)	(0.153)	(0.101)	(0.115)
$dbr_{k,t-1}$: Demand-based risk	-1.684^{***}	-1.149^{**}	-1.096^{**}	-1.397	-1.476^{***}
	(0.505)	(0.476)	(0.456)	(0.951)	(0.492)
$cs^r_{fk,t-1} \times \mathbb{1}[LowICR]_t$		-0.696^{***}	-0.653^{***}		
		(0.233)	(0.215)		
$dbr_{k,t-1} \times \mathbb{1}[LowICR]_t$			-0.171		
			(0.467)		
Controls	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
F-statistic	540.97	122.74	136.76	259.96	199.45
Observations	322,884	322,884	322,884	209,057	113,827
Note:			*p<0.1; **p<0.05; ***p<0.01		

Note: This table shows estimates of how firms respond to price dispersion split by different level of Intermediary Capital Ratio. High Intermediary Capital Ratio is classified by upper tercile across the full sample (67th percentile and higher), and Low Intermediary Capital Ratio is the rest of the sample (66th percentile and lower). The sample period is monthly from January 2008 to December 2023, considering the period for any positive outstanding of a given bond type k held by firm f. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The outcome variable is the amount issued for a given bond type k 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 (29) and (1), and their instruments are constructed from Equation (30) and (34). The firm-level controls include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

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A Merge method

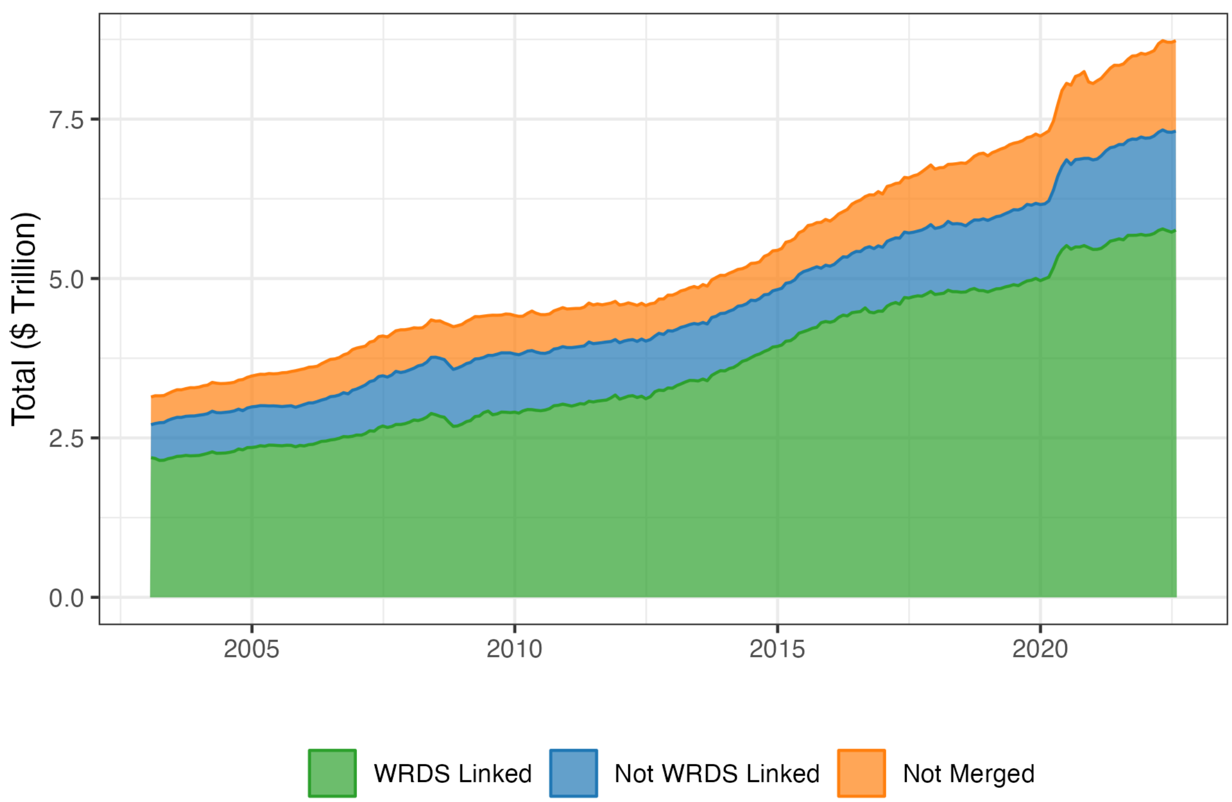
The main goal for the merge between FISD and Compustat was to add the gvkeys found in Compustat to the FISD data. The linked table should be issuer centered, i.e., each bond issuer entity should be linked only to one GVKEY at a point in time. Because each parent company, represented by the GVKEY, might 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 specially from the WRDS link, cusips and string match, and to deal with duplicates.

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.

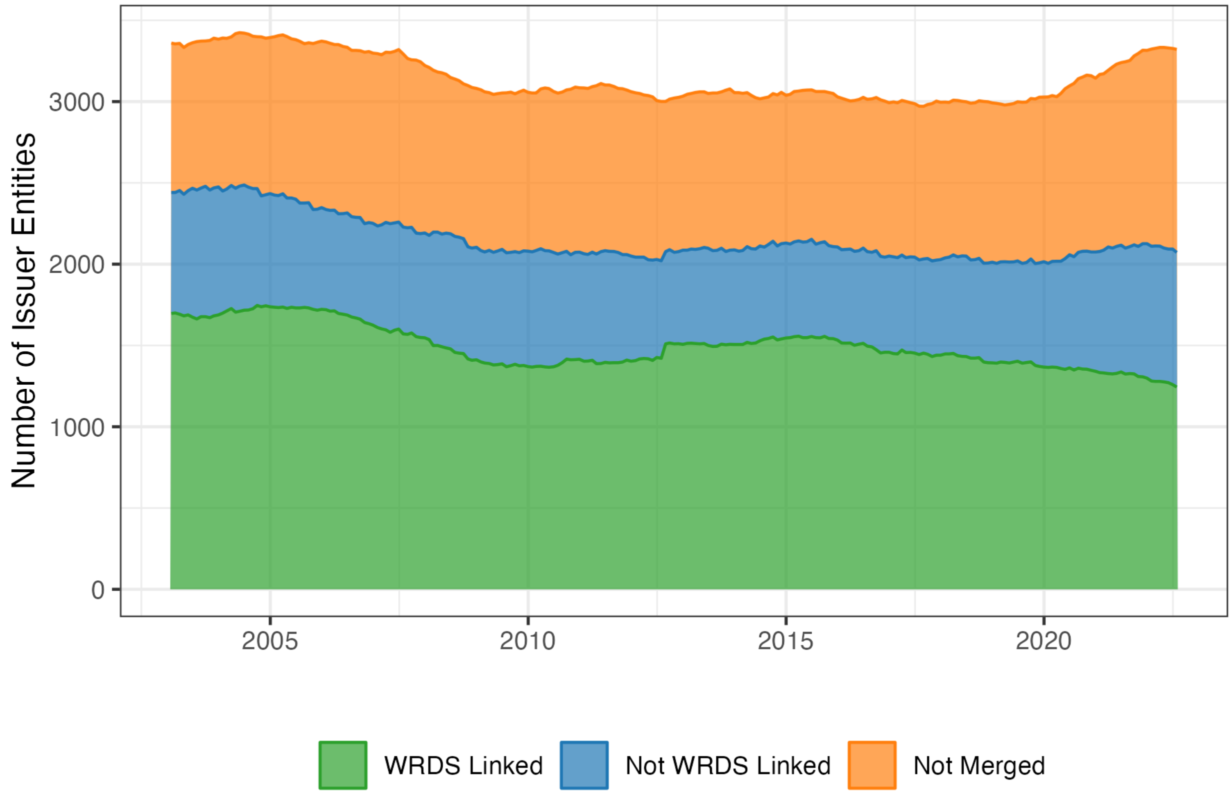
Because WRDS link is more likely to miss on smaller issuer, which many times are subsidiaries of rather than parent companies, it is also interesting to check the number of bond issuers in our final data. The summary is plotted in Figure A.2. As end of 2022, out of the 3321 issuers in the data, 1244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



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

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



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

B Definition of bond type

Table B.1: Summary Bond Types

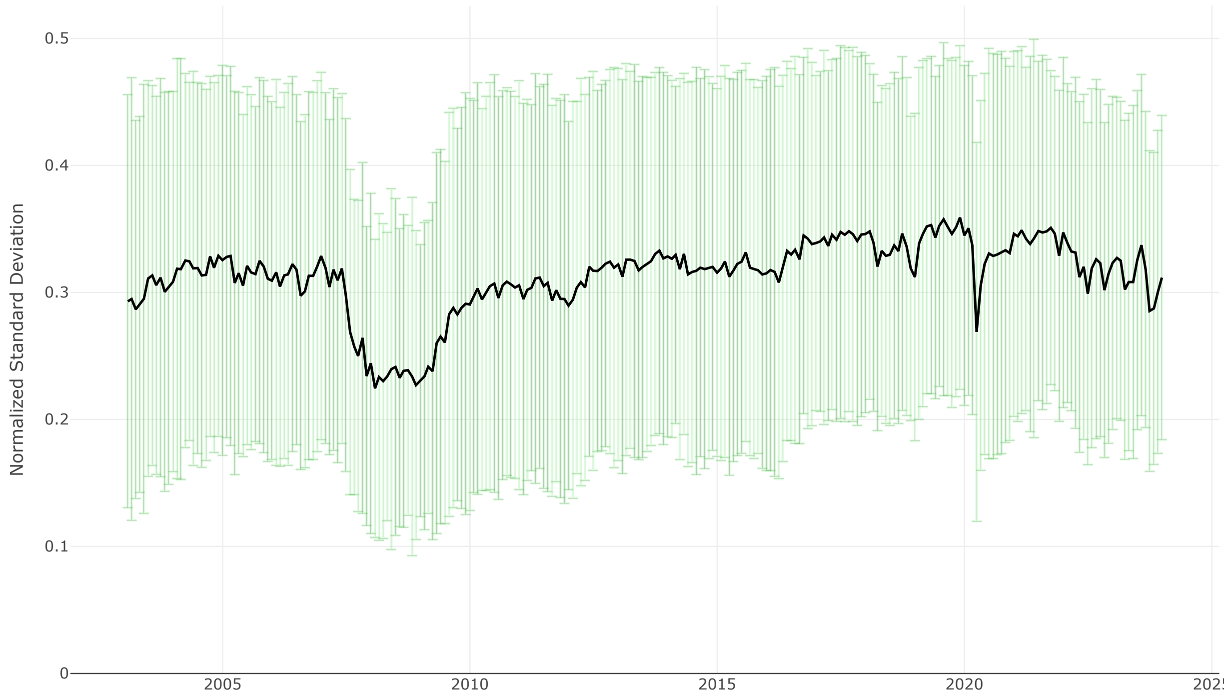
	bond_type_id	Average # bonds	10th Percentile	Median	90th Percentile
1	HY_0y3y_0m500m_TRUE_N	3,999	233	2,542	11,309
2	HY_0y3y_0m500m_TRUE_Y	2,468	77	500	7,992
3	A_0y3y_0m500m_TRUE_N	1,981	458	1,248	4,145
4	HY_3y10y_0m500m_TRUE_N	1,678	218	700	4,636
5	HY_3y10y_0m500m_TRUE_Y	1,527	383	545	4,740
6	HY_3y10y_0m500m_FALSE_Y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

Note: This table summarizes the all the bond types. 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 bond types that consistently have no more than 50 bonds into three or four dimensions.

B.1 Bond types and pice variation

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

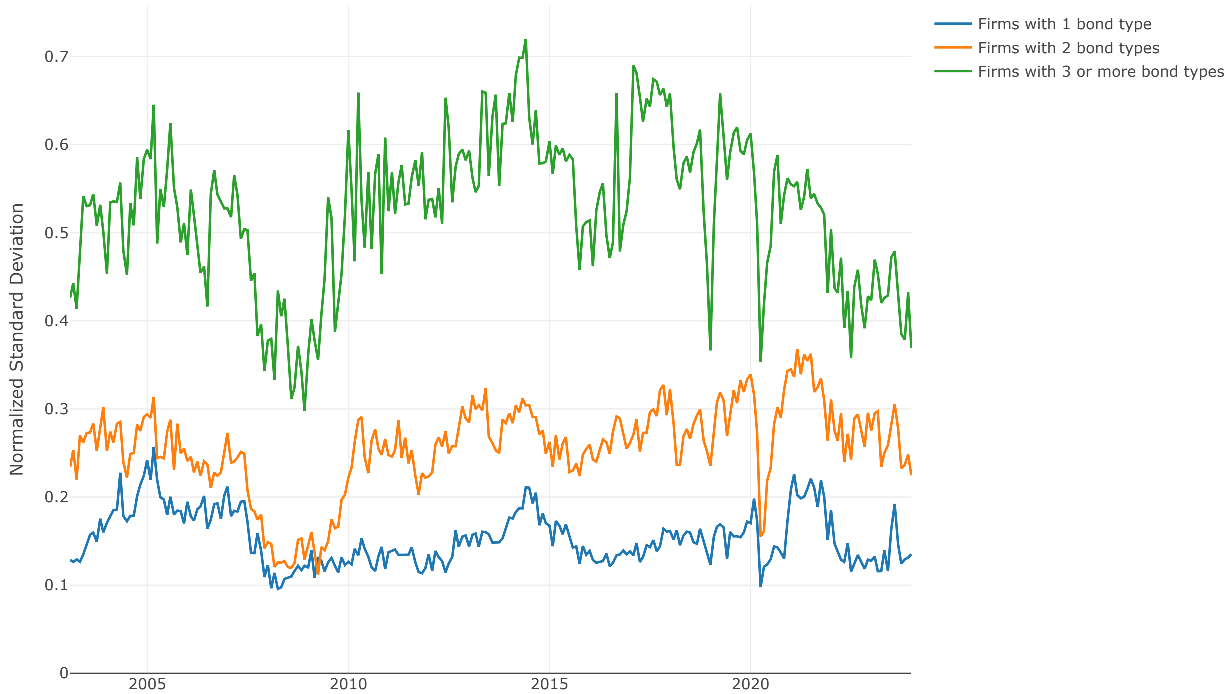
Figure B.1: Normalized Price Dispersion Overtime with Interquartile Range



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

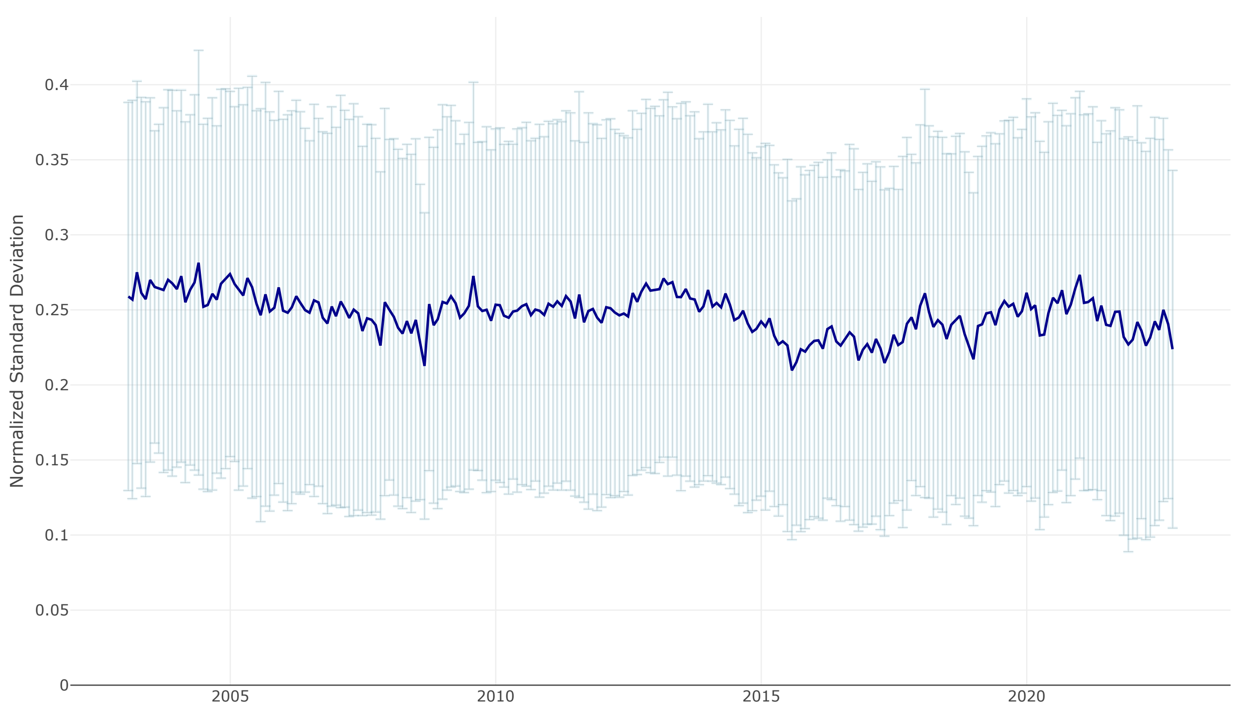
Clearly, prices should vary across bonds with differing maturities and ratings. However, these two characteristics, while important for explaining the price dispersion, do not explain all of it. Indeed, we show in Figure B.3 the remaining price dispersion when residualizing credit spreads with rating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

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



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

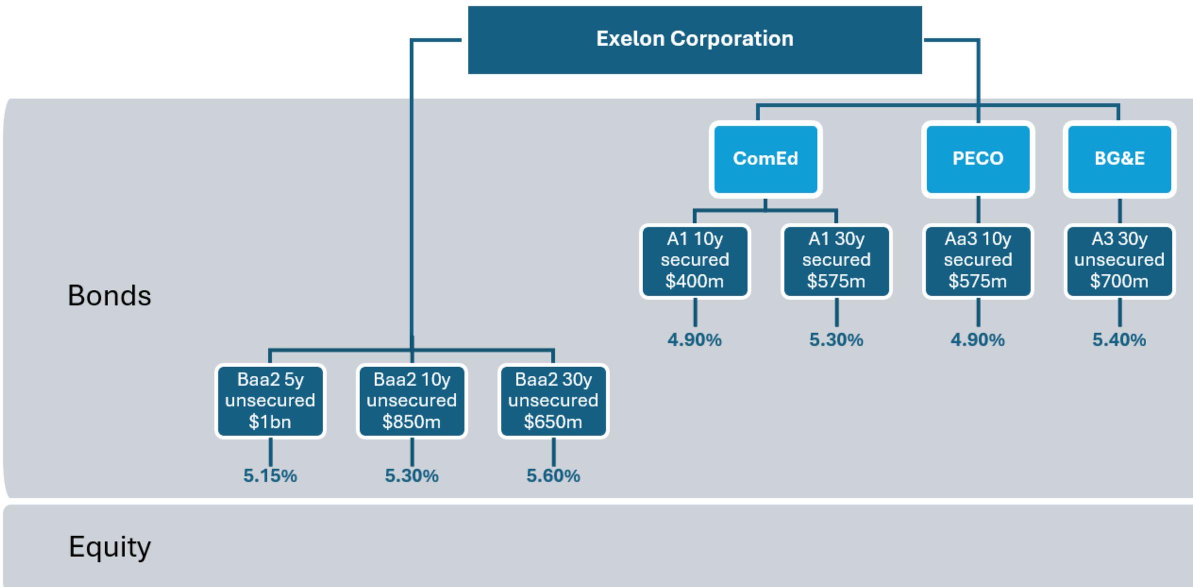
Figure B.3: Normalized Residual Price Dispersion Overtime with Interquartile Range



Note: This figure shows interquartile range of face-value weighted normalized standard deviations of residual credit spreads within a firm. Residual credit spread is defined as ϵ_{bft} in regression $cs_{bft} = \alpha_{rating,duration,t} + \epsilon_{bft}$. We category the duration into 5 buckets: < 1 year, 1 to 3 years, 3 to 7

C Extra data description

Figure C.1: Bonds issued by Exelon Corporation in 2023



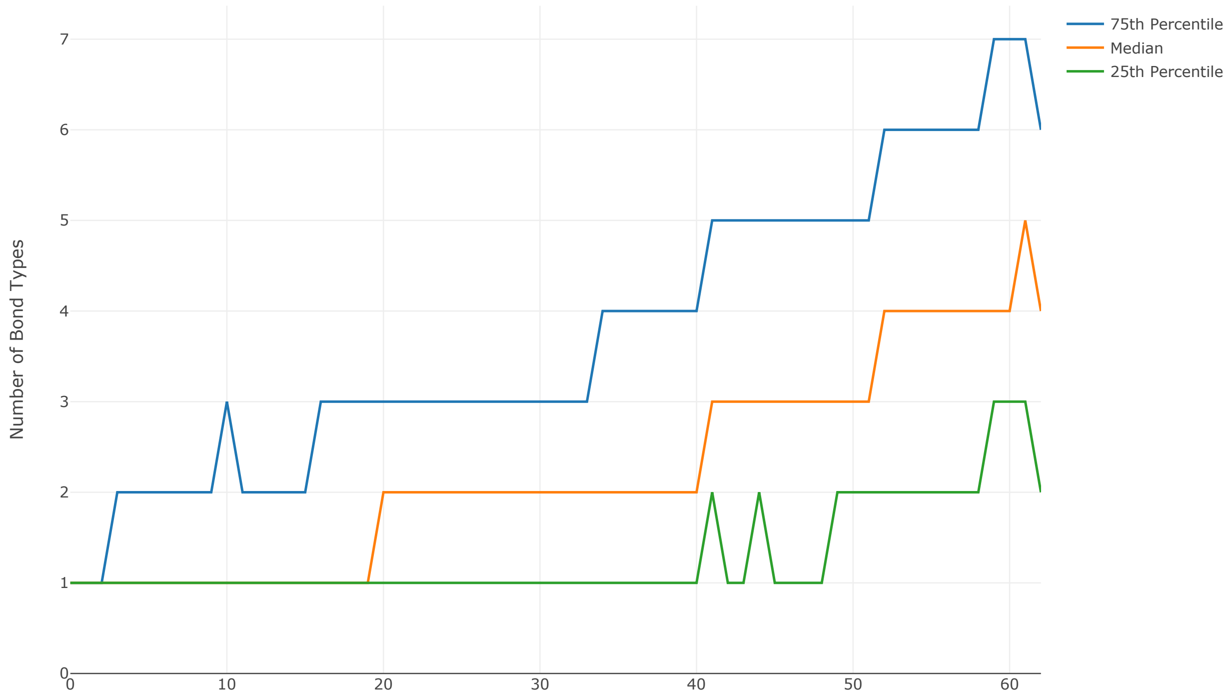
Note: This figure shows the debt issued by Exelon Corporation and its subsidiaries (i.e., Commonwealth Edison, PECO Energy, and Baltimore Gas & Electric) in 2023, conditional on bonds greater than $400 million at issuance. Coupon rates are presented below. Data source: Mergent FISD and Exelon Corporate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

Table C.1: Share of firms with multiple issuer IDs within industry

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

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

Figure C.2: Relationship between Firm Age and Number of Unique Bond Types



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

D Model proofs

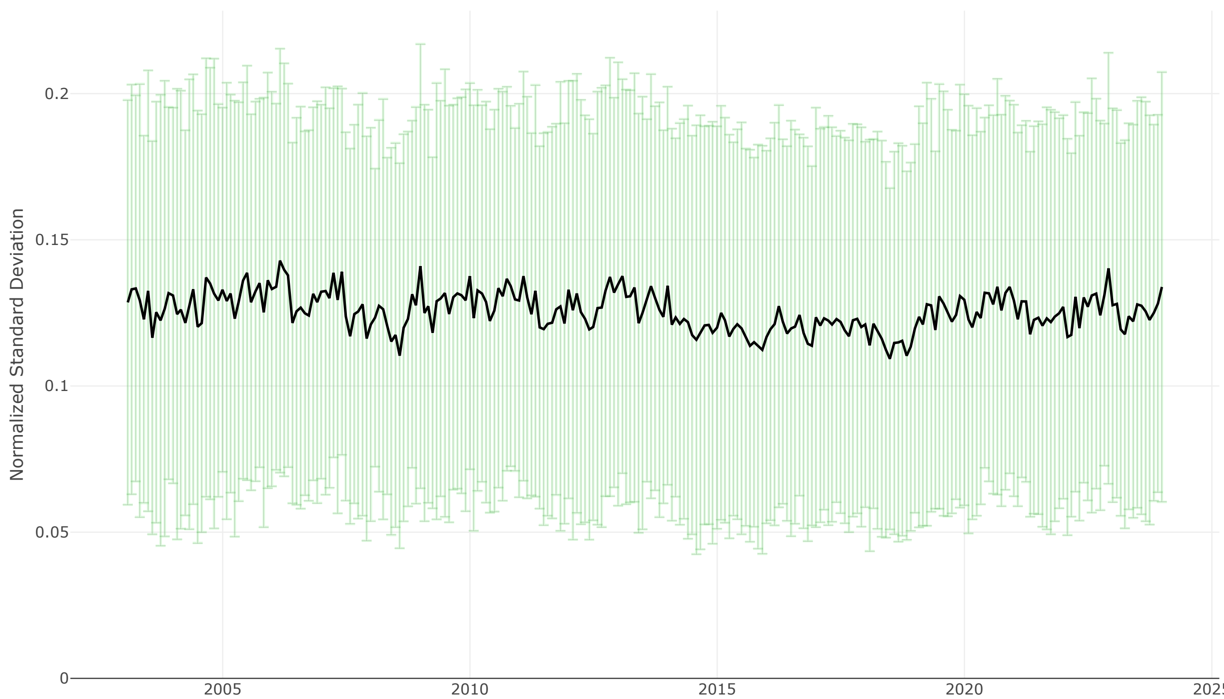
D.1 Deriving Equilibrium Prices

We begin with the investors' problem. In the model each investor i's wealth in period 1 is:

$$w_i' = q_{i,f} + q_{i,1}x_1 + q_{i,2}x_2 + w_i\theta_i\epsilon(s) \tag{40}$$

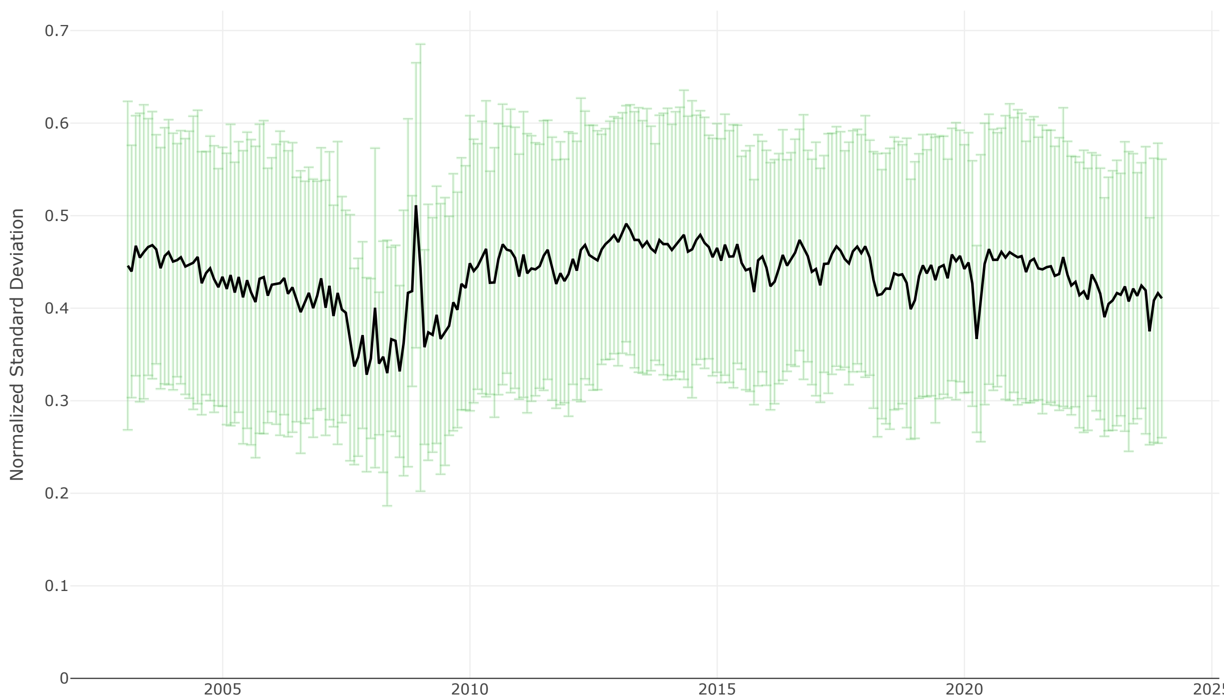
where x_1 is a Bernoulli variable that is realized when $\epsilon \geq c$, and x_2 is a Bernoulli variable that is realized when $\epsilon < C$. Also, ϵ follows a normal distribution: $\epsilon \sim \mathcal{N}(\mu, \sigma)$.

Figure C.3: Normalized Price Dispersion of Long-term Bonds



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

Figure C.4: Normalized Price Dispersion of Bonds Rated A



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

The investor faces a budget constraint in period 0:

$$w_i = q_{i,f} + p_1 q_{i,1} + p_2 q_{i,2}$$

Since this budget constraint always binds, we can rewrite the investor's question as the following:

$$\begin{aligned} &\max_{\{q_{i,1},q_{i,2}\}} U(q_{i,1}, q_{i,2}) \\ &s.t. \quad q_{i,1}, q_{i,2} \geq 0 \\ &\qquad\;\; w_i \geq q_{i,1}p_1 + q_{i,2}p_2 \end{aligned} \tag{41}$$

The investor's utility function is a mean-variance function, where

$$\begin{aligned} \mathbb{E}(w_{i'}) &= q_{i,1}(\pi - p_1) + q_{i,2}(1 - \pi - p_2) + w_i(1 + \theta_i \mu) \\ \text{Var}(w_{i'}) &= \pi(1 - \pi)(q_{i,1} - q_{i,2})^2 + (w_i \theta_i)^2 \sigma^2 + 2 w_i \theta_i \sigma \phi^* (q_{i,1} - q_{i,2}) \end{aligned} \tag{42}$$

Thus the investor's utility function is is

$$\begin{aligned} U(q_{i,1}, q_{i,2}) = &\; q_{i,1}(\pi - p_1) + q_{i,2}(1 - \pi - p_2) + w_i(1 + \theta_i \mu) \\ &- \gamma\big(\pi(1 - \pi)(q_{i,1} - q_{i,2})^2 + (w_i \theta_i)^2 \sigma^2 + 2 w_i \theta_i \sigma \phi^* (q_{i,1} - q_{i,2})\big) \end{aligned} \tag{43}$$

We can write the Lagrangian as

$$\mathcal{L} = U(q_{i,1}, q_{i,2}) + \lambda_{i1} q_{i,1} + \lambda_{i2} q_{i,2} + \lambda_{if}(w_{i,f} - q_{i,1}p_1 - q_{i,2}p_2) \tag{44}$$

Taking the agent's first order conditions with respect to the conditions we have

$$\frac{\partial \mathcal{L}}{\partial q_{i,1}} \; : \; \pi - p_1(1 + \lambda_{if}) - 2\gamma\pi(1 - \pi)(q_{i,1} - q_{i,2}) - 2\gamma w_i \theta_i \sigma \phi^* + \lambda_{i1} = 0 \tag{45}$$

$$\frac{\partial \mathcal{L}}{\partial q_{i,2}} \; : \; (1 - \pi) - p_2(1 + \lambda_{if}) + 2\gamma\pi(1 - \pi)(q_{i,1} - q_{i,2}) + 2\gamma w_i \theta_i \sigma \phi^* + \lambda_{i2} = 0 \tag{46}$$

and with complementary slackness,

$$\lambda_{i1} \geq 0,\ q_{i,1} \geq 0, \quad \lambda_{i1} q_{i,1} = 0$$
$$\lambda_{i2} \geq 0,\ q_{i,2} \geq 0, \quad \lambda_{i2} q_{i,2} = 0$$
$$\lambda_{if} \geq 0,\ q_{i,f} \geq 0, \quad \lambda_{if}(w_i - p_1 q_{i,1} - p_2 q_{i,2}) = 0$$

Following the same notation for shorthand we do in Section 3, we can then sum the first two first order conditions for agents A and B and use the market clearing condition in Eq. 12, and get:

$$(2 + \lambda_{A,f} + \lambda_{B,f})p_1 = 2\pi - 2\gamma\sigma_X^2(q_1 - q_2) - 2\gamma\sigma\phi\mathbb{A} - 2\gamma\sigma\phi\mathbb{B} + \lambda_{A1} + \lambda_{B1} \tag{47}$$
$$(2 + \lambda_{A,f} + \lambda_{B,f})p_2 = 2(1 - \pi) + 2\gamma\sigma_X^2(q_1 - q_2) + 2\gamma\sigma\phi\mathbb{A} + 2\gamma\sigma\phi\mathbb{B} + \lambda_{A2} + \lambda_{B2} \tag{48}$$

Note that we can also sum the foc's of each agent, as well as market clearing equations, to derive conditions on the Lagrange multipliers for each agent, λ_i's, as a function of prices:

$$p_1 + p_2 = \frac{1 + \lambda_{i1} + \lambda_{i2}}{1 + \lambda_{if}} \tag{49}$$

Going forwards we will define a value Λ^* that represents an alternate formulation:

$$\Lambda^* := 1 - p_1 - p_2 = \frac{-\lambda_{if} + \lambda_{i1} + \lambda_{i2}}{1 + \lambda_{if}} = \frac{-\lambda_{Af} - \lambda_{Bf} + \lambda_{A1} + \lambda_{B1} + \lambda_{A2} + \lambda_{B2}}{2 + \lambda_{Af} + \lambda_{Bf}} \tag{50}$$

This value may be pinned down by a combination of assumptions on zero and nonzero quantities of asset purchases.

D.2 Equilibrium Quantities

Equipped with an expression for equilibrium prices as a function of quantities, we can now turn to the firm's problem. The risk-averse firm chooses quantities of bonds to maximize the mean-variance weighted value of the bonds but takes prices as given. The value of the firm can thus be written as:

$$V(\mathbf{q}, \mathbf{p}; d) = \mathbb{E}[d + \mathbf{q}'(\mathbf{p} - \mathbf{x})] - \gamma_{\mathbf{f}}\text{Funding Risk} \tag{51}$$

We can write the Lagrangian as

$$\mathcal{L} = V(\mathbf{q}, \mathbf{p}; d) + \mu_1(q_1(p_1 - 1) + q_2 p_2 + d) + \mu_2(q_1 p_1 + q_2(p_2 - 1) + d) \tag{52}$$

Taking the firm's first order conditions we have

$$\frac{\partial \mathcal{L}}{\partial q_1} = 0 \implies p_1\left(1 + \mu_1 + \mu_2\right) - \gamma_f \frac{\partial \text{FR}}{\partial q_1} = \pi + \mu_1 \tag{53}$$

$$\frac{\partial \mathcal{L}}{\partial q_2} = 0 \implies p_2\left(1 + \mu_1 + \mu_2\right) - \gamma_f \frac{\partial \text{FR}}{\partial q_2} = 1 - \pi + \mu_2 \tag{54}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_1} \leq 0 \implies q_1(p_1 - 1) + q_2 p_2 + d \geq 0 \tag{55}$$

$$\frac{\partial \mathcal{L}}{\partial \mu_2} \leq 0 \implies q_1 p_1 + q_2(p_2 - 1) + d \geq 0 \tag{56}$$

We can write the last two inequalities as complementary slackness conditions:

$$-(q_1(p_1 - 1) + q_2 p_2 + d)\mu_1 = 0 \tag{57}$$

$$-(q_1 p_1 + q_2(p_2 - 1) + d)\mu_2 = 0 \tag{58}$$

With the exposition of the asset variance-covariance matrix as described in Section 3,

$$\tilde{\Sigma} = S'\Sigma S = \begin{bmatrix} \text{Var}(\tilde{\epsilon_1}) & \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) \\ \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) & \text{Var}(\tilde{\epsilon_2}) \end{bmatrix}$$

the funding risk is

$$FR = \mathbf{q}'\tilde{\Sigma}\mathbf{q} = q_1^2\text{Var}(\tilde{\epsilon_1}) + 2q_1q_2\text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2}) + q_2^2\text{Var}(\tilde{\epsilon_2}) \tag{59}$$

Suppose the firm's funding is always met by a sufficiently large value of d and the firm never faces insolvency issues. Then the firm's foc's reduce to:

$$\frac{\partial V}{\partial q_1} \quad : \quad p_1 - \pi - \gamma_f(2q_1\text{Var}(\tilde{\epsilon_1}) + 2q_2\text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2})) = 0 \tag{60}$$

$$\frac{\partial V}{\partial q_2} \quad : \quad p_2 - (1-\pi) - \gamma_f(2q_2\text{Var}(\tilde{\epsilon_2}) + 2q_1\text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2})) = 0 \tag{61}$$

Combining the firm's foc's, the agents' foc's, and the market clearing conditions, we can derive equilibrium values based on Λ^*:

$$\begin{aligned} q_1 = &\frac{\Lambda^*}{2\gamma_f \cdot \text{Var}(\tilde{\epsilon}_1+\tilde{\epsilon}_2)} + \frac{1}{2\gamma\sigma_X^2}\frac{\text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})} \cdot [(1-\pi)(\lambda_{Af}+\lambda_{Bf}) - (\lambda_{A2}+\lambda_{B2}) - 2\gamma\sigma\phi(\mathbb{A}+\mathbb{B})] \\ &- \frac{1}{2\gamma\sigma_X^2}\frac{\text{Var}(\tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})} \cdot [\pi(\lambda_{Af}+\lambda_{Bf}) - (\lambda_{A1}+\lambda_{B1}) + 2\gamma\sigma\phi(\mathbb{A}+\mathbb{B})] \end{aligned} \tag{62}$$

$$\begin{aligned} q_2 = &\frac{\Lambda^*}{2\gamma_f \cdot \text{Var}(\tilde{\epsilon}_1+\tilde{\epsilon}_2)} + \frac{1}{2\gamma\sigma_X^2}\frac{\text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})} \cdot [\pi(\lambda_{Af}+\lambda_{Bf}) - (\lambda_{A1}+\lambda_{B1}) + 2\gamma\sigma\phi(\mathbb{A}+\mathbb{B})] \\ &- \frac{1}{2\gamma\sigma_X^2}\frac{\text{Var}(\tilde{\epsilon_1})}{\text{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})} \cdot [(1-\pi)(\lambda_{Af}+\lambda_{Bf}) - (\lambda_{A2}+\lambda_{B2}) - 2\gamma\sigma\phi(\mathbb{A}+\mathbb{B})] \end{aligned} \tag{63}$$

$$p_1 = \pi + \frac{\text{Var}(\tilde{\epsilon_1}) + \text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})} \cdot \Lambda^* \tag{64}$$

$$p_2 = (1-\pi) + \frac{\text{Var}(\tilde{\epsilon_2}) + \text{Cov}(\tilde{\epsilon_1},\tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})} \cdot \Lambda^* \tag{65}$$

See below for how we derive the value Λ^*.

D.3 Deriving equilibrium for symmetric investors

$$\max_{\{q_{i1},q_{i2}\}} \mathbb{E}\left[w_i'\right] - \gamma \mathbb{V}\left[w_i'\right] \tag{66}$$

$$\begin{aligned} s.t. \quad & q_{i1}, q_{i2} \geq 0 \text{ (no short-selling)} \\ & q_{i1}p_1 + q_{i2}p_2 \leq w_i \text{ (no borrowing)} \end{aligned} \tag{67}$$

Suppose $\theta_A < 0, \theta_B > 0$, with market segmentation. Then we can assume:

$$\begin{aligned} q_{A1} &> 0 & \lambda_{A1} &= 0 \\ q_{A2} &= 0 & \lambda_{A2} &\neq 0 \\ q_{B1} &= 0 & \lambda_{B1} &\neq 0 \\ q_{B2} &> 0 & \lambda_{B2} &= 0 \end{aligned} \tag{68}$$

Taking the agent's first order conditions we have

$$\frac{\partial \mathcal{L}}{\partial q_{i,1}} = 0 \implies (1+\lambda_{if})p_1 = \pi - 2\gamma\pi(1-\pi)(q_{i1}-q_{i2}) - 2\gamma w_i \theta_i \phi^* \sigma - \lambda_{i1} \tag{69}$$

$$\frac{\partial \mathcal{L}}{\partial q_{i,2}} = 0 \implies (1+\lambda_{if})p_2 = (1-\pi) + 2\gamma\pi(1-\pi)(q_{i1}-q_{i2}) + 2\gamma w_i \theta_i \phi^* \sigma - \lambda_{i2} \tag{70}$$

and

$$\lambda_{A2} = \lambda_{B1} = p_1 + p_2 - 1 = \Lambda^*$$

Solving the foc's yields

$$q_{A1} = \frac{\pi - (1+\lambda_{Af})p_1}{\gamma\sigma_X^2} - \frac{2\gamma\phi\sigma\mathbb{A} - \lambda_{A1}}{2\gamma\sigma_X^2}, \quad q_{A2} = 0 \tag{71}$$

$$q_{B1} = 0, \quad q_{B2} = \frac{1-\pi-(1+\lambda_{Bf})p_2}{\gamma\sigma_X^2} + \frac{2\gamma\phi\sigma\mathbb{B} + \lambda_{B2}}{2\gamma\sigma_X^2} \tag{72}$$

Imposing market clearing, so that $q_{A1} = q_1$, $q_{B2} = q_2$, we may simplify

$$p_1 = \pi - 2\gamma\pi(1-\pi)q_1 - 2\gamma\phi^*\sigma\mathbb{A} \tag{73}$$

$$p_2 = 1 - \pi - 2\gamma\pi(1-\pi)q_2 + 2\gamma\phi^*\sigma\mathbb{B} \tag{74}$$

Recall the firm's foc's from Section D.2, which we may simplify to:

$$p_1 = \pi + 2\gamma_f(q_1\mathrm{Var}(\tilde{\epsilon_1}) + q_2\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})) \tag{75}$$

$$p_2 = (1-\pi) + 2\gamma_f(q_2\mathrm{Var}(\tilde{\epsilon_2}) + q_1\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})) \tag{76}$$

Combining this system of equations yields:

$$q_1^* = -\frac{\sigma\phi}{\sigma_X^2}\cdot\frac{\gamma\sigma_X^2\mathbb{A} + \gamma_f\mathrm{Var}(\tilde{\epsilon_2})\mathbb{A} + \gamma_f\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})\mathbb{B}}{\gamma\sigma_X^2 + \gamma_f\mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f\mathrm{Var}(\tilde{\epsilon_2})} \tag{77}$$

$$q_2^* = \frac{\sigma\phi}{\sigma_X^2}\cdot\frac{\gamma\sigma_X^2\mathbb{B} + \gamma_f\mathrm{Var}(\tilde{\epsilon_1})\mathbb{B} + \gamma_f\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})\mathbb{A}}{\gamma\sigma_X^2 + \gamma_f\mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f\mathrm{Var}(\tilde{\epsilon_2})} \tag{78}$$

$$p_1^* = \pi + 2\gamma\gamma_f\sigma\phi\frac{\mathbb{B}\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) - \mathbb{A}\mathrm{Var}(\tilde{\epsilon_1})}{\gamma\sigma_X^2 + \gamma_f\mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f\mathrm{Var}(\tilde{\epsilon_2})} \tag{79}$$

$$p_2^* = 1 - \pi - 2\gamma\gamma_f\sigma\phi\frac{\mathbb{A}\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) - \mathbb{B}\mathrm{Var}(\tilde{\epsilon_2})}{\gamma\sigma_X^2 + \gamma_f\mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f\mathrm{Var}(\tilde{\epsilon_2})} \tag{80}$$

where

$$\mathbb{A} = w_A\theta_A, \quad \mathbb{B} = w_B\theta_B \quad \text{and} \quad \sigma_X^2 = \pi(1-\pi),$$

$$\phi^* = \phi\Big(\frac{c-\mu}{\sigma}\Big), \quad \epsilon \sim \mathcal{N}(\mu, \sigma)$$

Note again that since $\theta_A < 0$, $\theta_B > 0$, we have $\mathbb{A} < 0$, $\mathbb{B} > 0$.

We can also derive

$$\Lambda^* = p_1 + p_2 - 1 = 2\gamma\sigma\phi\gamma_f\frac{\sigma^2(\mathbb{A}+\mathbb{B})^2(\mathbb{B}-\mathbb{A})}{\gamma\sigma_X^2 + \gamma_f\mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f\mathrm{Var}(\tilde{\epsilon_2})} \tag{81}$$

where this will always be greater than 0 with the assumptions $\theta_A < 0, \theta_B > 0$. Thus the assumptions are a sufficient condition for market segmentation. We additionally note that in the case that the θs are not of opposite signs, it is still possible for agent A to only purchase asset 1 and agent B to only purchase asset B if the wealth-weighted exposure of B outweighs that of A.

D.4 Deriving Value of the Firm

The value of the firm is defined as

$$V(q_1, q_2, p_1, p_2; d) = \mathbb{E}[d + \mathbf{q}'(\mathbf{p} - \mathbf{x})] - \gamma_f \text{FR} \tag{82}$$

which in nonmatrix form here is

$$V^* = d + \underbrace{q_1(p_1 - \pi) + q_2(p_2 - (1 - \pi))}_{\Pi} - \gamma_f \text{FR} \tag{83}$$

Consider the equations that we have derived in Section D.2. More importantly, let us use shorthand for two parts:

$$\Omega_{1-\pi,2} = [(1 - \pi)(\lambda_{Af} + \lambda_{Bf}) - (\lambda_{A2} + \lambda_{B2}) - 2\gamma\sigma\phi(\mathbb{A} + \mathbb{B})] \tag{84}$$

$$\Omega_{\pi,1} = [\pi(\lambda_{Af} + \lambda_{Bf}) - (\lambda_{A1} + \lambda_{B1}) + 2\gamma\sigma\phi(\mathbb{A} + \mathbb{B})] \tag{85}$$

which importantly lets us rewrite:

$$q_1^* = \frac{1}{2\gamma_f \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^* + \frac{1}{2\gamma\sigma_X^2}\frac{\text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Omega_{1-\pi,2} - \frac{1}{2\gamma\sigma_X^2}\frac{\text{Var}(\tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Omega_{\pi,1} \tag{86}$$

$$q_2^* = \frac{1}{2\gamma_f \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^* + \frac{1}{2\gamma\sigma_X^2}\frac{\text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Omega_{\pi,1} - \frac{1}{2\gamma\sigma_X^2}\frac{\text{Var}(\tilde{\epsilon_1})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Omega_{\pi,1} \tag{87}$$

and

$$p_1^* = \pi + \frac{\text{Var}(\tilde{\epsilon_1}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^*$$
$$p_2^* = (1-\pi) + \frac{\text{Var}(\tilde{\epsilon_2}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^*$$

Once we multiply the per-unit profit on assets 1 and 2 by the quantities sold of assets 1 and 2 respectively, we notice that we can group together the Ωs and that they cancel out, since $\text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})^2 = \text{Var}(\tilde{\epsilon_1}) * \text{Var}(\tilde{\epsilon_2})$ in our construction. Then

$$\begin{aligned}\Pi =& q_1^* * (p_1^* - \pi) + q_2^* * (p_2^* - (1-\pi)) \\ =& \frac{1}{2\gamma_f \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^{*2}\Big(\frac{\text{Var}(\tilde{\epsilon_1}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})} + \frac{\text{Var}(\tilde{\epsilon_2}) + \text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2})}{\text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Big) \\ =& \frac{1}{2\gamma_f \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^{*2}\end{aligned} \tag{88}$$

and we calculate the funding risk as

$$\begin{aligned}FR &= q_1^2 \text{Var}(\tilde{\epsilon_1}) + 2\text{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) q_1 q_2 + q_2^2 \text{Var}(\tilde{\epsilon_2}) \\ &= (s_{A1}\mathbb{A} + s_{B1}\mathbb{B})^2 \sigma^2 q_1^2 + (s_{A1}\mathbb{A} + s_{B1}\mathbb{B})(s_{A2}\mathbb{A} + s_{B2}\mathbb{B})\sigma^2 q_1 q_2 + (s_{A2}\mathbb{A} + s_{B2}\mathbb{B})^2 \sigma^2 q_2^2 \\ &= [(s_{A1}\mathbb{A} + s_{B1}\mathbb{B})\sigma q_1 + (s_{A2}\mathbb{A} + s_{B2}\mathbb{B})\sigma q_2]^2 \\ &= [\sqrt{\text{Var}(\tilde{\epsilon_1})} q_1 + \sqrt{\text{Var}(\tilde{\epsilon_2})} q_2]^2\end{aligned}$$

Similarly, we can group together the Ωs and they cancel out once more, leaving

$$FR = [\frac{\sqrt{\text{Var}(\tilde{\epsilon_1})}}{2\gamma_f \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^* + \frac{\sqrt{\text{Var}(\tilde{\epsilon_2})}}{2\gamma_f \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^*]^2 = \frac{1}{4\gamma_f^2 \text{Var}(\tilde{\epsilon_1} + \tilde{\epsilon_2})}\Lambda^{*2} \tag{89}$$

Then

$$
\begin{aligned}
V &= d + \Pi - \gamma_f \mathrm{FR} &(90)\\
&= d + \frac{1}{2\gamma_f \mathrm{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})}\Lambda^{*2} - \gamma_f \frac{1}{4\gamma_f^2 \mathrm{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})}\Lambda^{*2} = d + \frac{1}{4\gamma_f \mathrm{Var}(\tilde{\epsilon_1}+\tilde{\epsilon_2})}\Lambda^{*2} &(91)\\
&= d + \gamma_f \left(\gamma\sigma^2\phi \frac{\mathbb{A}^2 - \mathbb{B}^2}{\gamma\sigma_X^2 + \gamma_f \mathrm{Var}(\tilde{\epsilon_1}) + \gamma_f \mathrm{Var}(\tilde{\epsilon_2})}\right)^2 &(92)
\end{aligned}
$$

D.5 Deriving the hypotheses

Hypothesis 1.

$$
\frac{\partial p_1^*}{\partial \mathbb{A}} = -2\gamma\phi^*\sigma \frac{\gamma_f\sigma^2}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2+\mathbb{B}^2)}\Big((\mathbb{A}^2 - \mathbb{B}^2) + \frac{2\mathbb{A}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2+\mathbb{B}^2)}\Big) \tag{93}
$$

If

$$
\begin{aligned}
\mathbb{A}^2 + \frac{2\mathbb{A}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2+\mathbb{B}^2)} < \mathbb{B}^2 \quad &\longrightarrow \quad \frac{\partial p_1^*}{\partial \mathbb{A}} > 0, \quad \text{i.e.} \quad \frac{\partial p_1^*}{\partial |\mathbb{A}|} < 0\\
\mathbb{A}^2 + \frac{2\mathbb{A}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{B}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2+\mathbb{B}^2)} > \mathbb{B}^2 \quad &\longrightarrow \quad \frac{\partial p_1^*}{\partial \mathbb{A}} < 0, \quad \text{i.e.} \quad \frac{\partial p_1^*}{\partial |\mathbb{A}|} > 0
\end{aligned}
$$

$$
\frac{\partial p_1^*}{\partial \mathbb{B}} = 2\gamma\phi^*\sigma\mathbb{A} \cdot \frac{2\gamma_f\sigma^2\mathbb{B}(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{A}^2)}{(\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2+\mathbb{B}^2))^2} < 0 \tag{94}
$$

$$
\frac{\partial p_2^*}{\partial \mathbb{A}} = -2\gamma\phi^*\sigma\mathbb{B} \cdot \frac{2\gamma_f\sigma^2\mathbb{A}(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{B}^2)}{(\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2+\mathbb{B}^2))^2} > 0 \tag{95}
$$

where again signs flip with magnitude, so

$$
\frac{\partial p_2^*}{\partial \mathbb{A}} > 0, \quad \text{i.e.} \quad \frac{\partial P_2^*}{\partial |\mathbb{A}|} < 0
$$

$$\frac{\partial p_2^*}{\partial \mathbb{B}} = -2\gamma\phi^*\sigma \frac{\gamma_f \sigma^2}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)}\Big((\mathbb{A}^2 - \mathbb{B}^2) - \frac{2\mathbb{B}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{A}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)}\Big) \tag{96}$$

If

$$\mathbb{B}^2 + \frac{2\mathbb{B}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{A}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)} < \mathbb{A}^2 \quad \longrightarrow \quad \frac{\partial p_2^*}{\partial \mathbb{B}} = \frac{\partial p_2^*}{\partial |\mathbb{B}|} < 0$$

$$\mathbb{B}^2 + \frac{2\mathbb{B}^2(\gamma\sigma_X^2 + 2\gamma_f\sigma^2\mathbb{A}^2)}{\gamma\sigma_X^2 + \gamma_f\sigma^2(\mathbb{A}^2 + \mathbb{B}^2)} > \mathbb{A}^2 \quad \longrightarrow \quad \frac{\partial p_2^*}{\partial \mathbb{B}} = \frac{\partial p_2^*}{\partial |\mathbb{B}|} > 0$$

Hypothesis 2.

$$\frac{\partial q_i^*}{\partial p_i} = \frac{1}{2\gamma_f \mathrm{Var}(\tilde{\epsilon}_i)} > 0$$

Hypothesis 3.

Since

$$\mathrm{Var}(\tilde{\epsilon_1}) = (s_{A1}\mathbb{A} + s_{B1}\mathbb{B})^2\sigma^2$$

$$\mathrm{Var}(\tilde{\epsilon_2}) = (s_{A2}\mathbb{A} + s_{B2}\mathbb{B})^2\sigma^2$$

$$\mathrm{Cov}(\tilde{\epsilon_1}, \tilde{\epsilon_2}) = (s_{A1}\mathbb{A} + s_{B1}\mathbb{B})(s_{A2}\mathbb{A} + s_{B2}\mathbb{B})\sigma^2$$

$$q_1 = \frac{1}{2\mathrm{Var}(\tilde{\epsilon_1})}\Big(\frac{p_1 - \pi}{\gamma_f} - 2q_2\sqrt{\mathrm{Var}(\tilde{\epsilon_1})} \cdot \sqrt{vart}\Big)$$

thus

$$\frac{\partial q_1}{\partial \mathrm{Var}(\tilde{\epsilon_1})} = -\frac{1}{2\mathrm{Var}(\tilde{\epsilon_1})^2}\Big(\frac{p_1 - \pi}{\gamma_f} + q_2\sqrt{\mathrm{Var}(\tilde{\epsilon_1})} \cdot \sqrt{\mathrm{Var}(\tilde{\epsilon_2})}\Big)$$

$$\frac{\partial q_j}{\partial \mathrm{Var}(\tilde{\epsilon_j})} = -\frac{1}{2\mathrm{Var}(\tilde{\epsilon_j})^2}\Big(\frac{p_j - \mathbb{E}[p_j]}{\gamma_f} + q_i\sqrt{\mathrm{Var}(\tilde{\epsilon_j})} \cdot \sqrt{\mathrm{Var}(\tilde{\epsilon_i})}\Big)$$

E Extra Results on the Issuance Analyses

E.1 Simple OLS

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

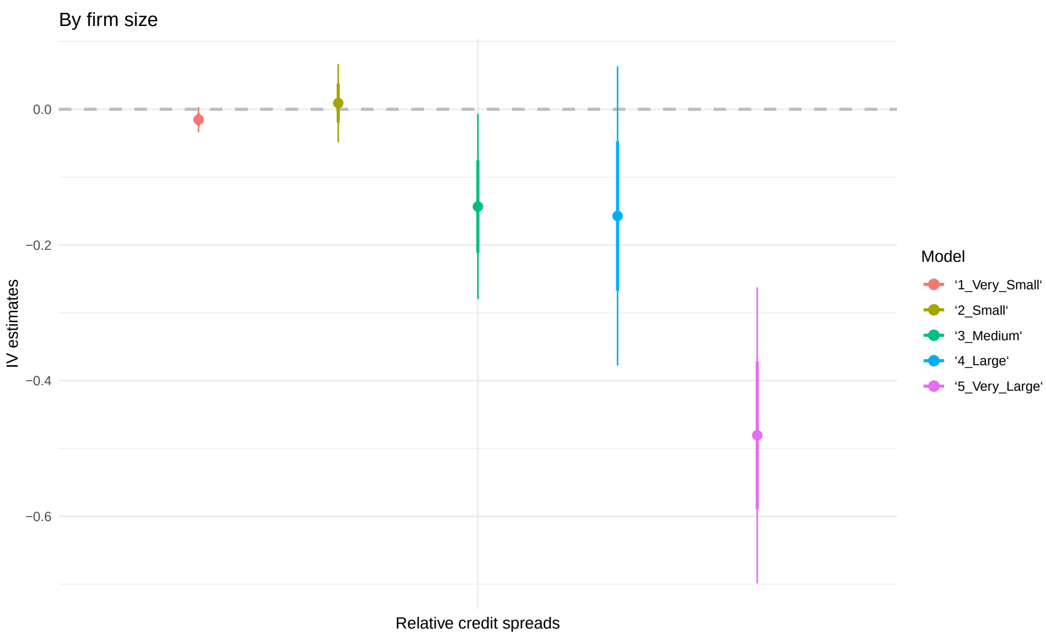
	$issuance_{fkt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fk,t-1}$: Relative bond-type credit spread	0.005^{*}	-0.00002			0.009^{***}	0.004
	(0.003)	(0.004)			(0.003)	(0.004)
$dbr_{k,t-1}$: Relative demand-based risk			1.749^{***}	1.898^{***}	1.753^{***}	1.900^{***}
			(0.102)	(0.105)	(0.102)	(0.105)
$Tobin's\ Q_{f,t-1}$	0.048^{***}		0.046^{***}		0.046^{**}	
	(0.018)		(0.018)		(0.018)	
$Leverage_{f,t-1}$	-0.055^{***}		-0.064^{***}		-0.064^{***}	
	(0.014)		(0.014)		(0.014)	
$Debt\ coming\ due_{f,t-1}$	0.613^{***}		0.617^{***}		0.617^{***}	
	(0.078)		(0.078)		(0.078)	
$Average\ CDS_{f,t-1}$	-0.056		-0.065		-0.068	
	(0.079)		(0.082)		(0.082)	
$Log\ assets_{f,t-1}$	-0.016^{***}		-0.016^{***}		-0.016^{***}	
	(0.003)		(0.003)		(0.003)	
Firm FE	✓		✓		✓	
Month FE	✓		✓		✓	
Firm × Month FE		✓		✓		✓
Observations	322,884	322,884	322,884	322,884	322,884	322,884
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 k in period t. The sample period is quarterly from 2008 Q1 to 2023 Q4, considering the period of any positive outstanding for a given bond type k held by firm f. The sample includes non-financials firms that had multiple bond types outstanding in the previous period, conditional on positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The outcome variable is the amount issued for a given bond type k 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 (29). The firm-level characteristics in the previous period include Tobin's Q, leverage (financial-debt-to-assets ratio), average CDS spread, debt coming due, and funding risk. Data is sourced from FISD, Compustat, WRDS Bond Returns, and Markit CDS. We winsorize all the variables at 1% and 99% to remove outliers.

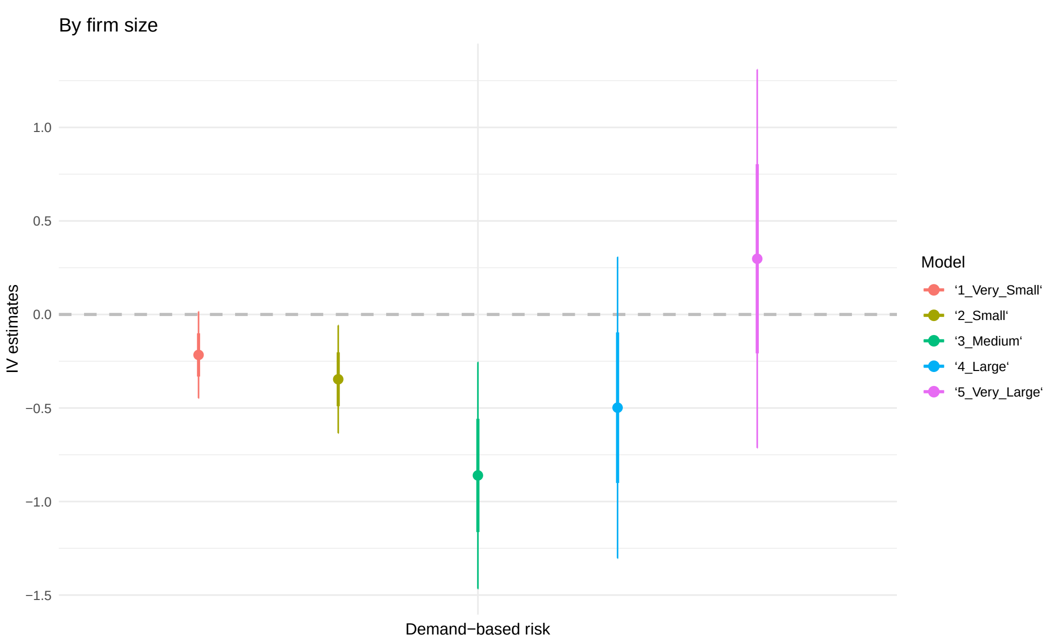
E.2 IV heterogeneous effects

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

a. Second-stage estimates on relative credit spreads



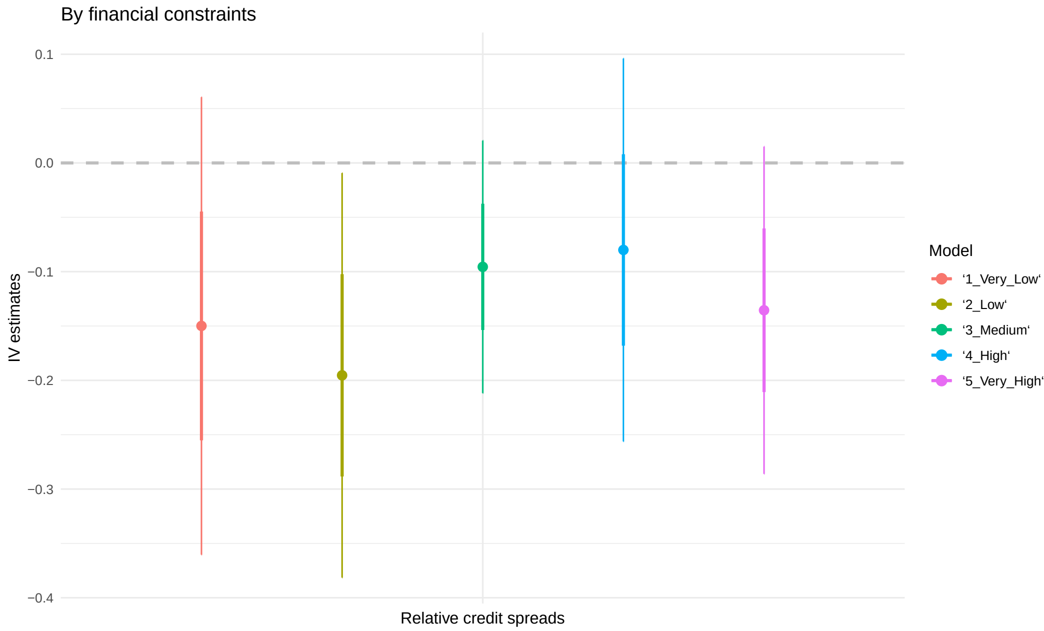
b. Second-stage estimates on demand-based risk



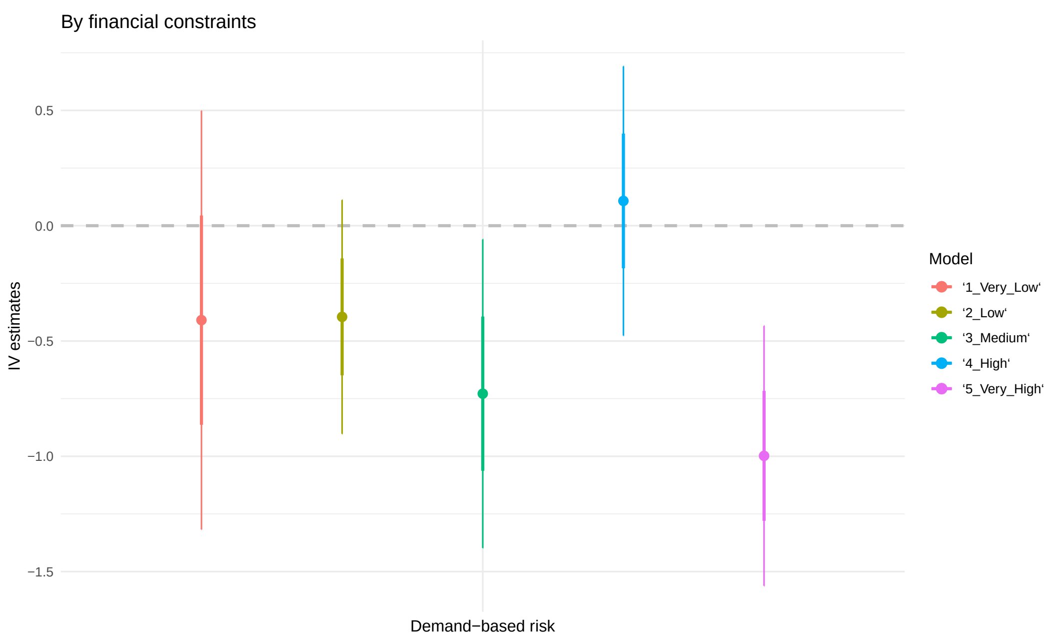
Note: This figure shows the IV heterogeneous effects, subsampling by firms' size in the prior period. The endogenous variables are constructed from Equation (29) and (1). The instrument variables are constructed from Equation (30) and (34). We control for firm characteristics including Tobin's Q, leverage, average CDS, debt coming due, and log assets in the previous period. Firm fixed effect and month fixed effect are included. Data is monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

Figure E.2: IV heterogeneous effects: subsample by financial constraints

a. Second-stage estimates on relative credit spreads



b. Second-stage estimates on demand-based risk



Note: This figure shows the IV heterogeneous effects, subsampling by firms' level of financial constraints in the prior period. The endogenous variables are constructed from Equation (29) and (1). The instrument variables are constructed from Equation (30) and (34). 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 monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

E.3 Extensive margin: Issuing a new bond type

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

	$\mathbb{1}[new\_bondtype]_{fkt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fk,t-1}$: Relative bond-type credit spread	-0.096^{***}	-0.063^{***}			-0.085^{***}	-0.060^{**}
	(0.019)	(0.020)			(0.019)	(0.025)
$dbr_{k,t-1}$: Relative demand-based risk			−0.147	−0.202	−0.115	−0.039
			(0.108)	(0.127)	(0.111)	(0.152)
$Tobin's\ Q_{f,t-1}$	0.002		0.0002		0.002	
	(0.005)		(0.004)		(0.004)	
$Leverage_{f,t-1}$	−0.004		−0.005		−0.004	
	(0.004)		(0.004)		(0.004)	
$Debt\ coming\ due_{f,t-1}$	0.114^{***}		0.106^{***}		0.113^{***}	
	(0.022)		(0.021)		(0.022)	
$Average\ CDS_{f,t-1}$	0.032		0.0004		0.029	
	(0.023)		(0.019)		(0.022)	
$Log\ assets_{f,t-1}$	-0.001^{**}		-0.002^{**}		-0.001^{**}	
	(0.001)		(0.001)		(0.001)	
Firm FE	✓		✓		✓	
Month FE	✓		✓		✓	
Firm × Month FE		✓		✓		✓
F-statistic	96.69	360.7	745.4	137.65	407.93	243.36
Observations	322,884	322,884	322,884	322,884	322,884	322,884

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

Note: This table shows how variation in demand-based risk would impact firm's decision of issuing a new bond type, conditional on prices. The sample period is monthly from January 2008 to December 2023, considering the period of any positive outstanding for a given bond type k held by firm f. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The independent variable $\mathbb{1}[new\_bondtype]_{ft} = 1$ if the firm f has no outstanding for bond type k in the past 12 months. The endogenous variables are constructed from Equation (29) and (1). The instrument variables are constructed from Equation (30) and (34). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

E.4 Alternative measure of demand based risk: ΔFR

One issue of dbr_{kt} is that it only incorporates the variance of the demand based risk, and not the covariance structure. We test the robustness of the results by introducing an alternative measure

ΔFR defined as:

$$\Delta FR_{fkt} = \mathbb{1}_k' \underbrace{\Sigma_t}_{K \times K} \underbrace{q_{ft}}_{K \times 1} \tag{97}$$

where q_{ft} is a $K \times 1$ vector of firm's holdings share for each bond-type, normalized by its contemporaneous total assets. See Appendix H for detailed construction of the measure.

Table E.3: How relative credit spreads and funding risks affect firms net issuance

Panel A: First stage test for flow-based instruments

	$cs^{r}_{fk,t-1}$		$\Delta FR_{fk,t-1}$		$cs^{r}_{fk,t-1}$	
	(1)	(2)	(3)	(4)	(5)	(6)
$z^{cs}_{k,t-1}$	-15.168^{***}	-18.725^{***}			-16.098^{***}	-17.763^{***}
	(0.427)	(0.522)			(0.436)	(0.534)
$z^{\Delta FR}_{fk,t-1}$			11.499^{***}	5.937^{***}	-3.840^{***}	4.561^{***}
			(0.063)	(0.063)	(0.356)	(0.544)
$Tobin's\ Q_{f,t-1}$	0.019^{***}		0.020^{***}		0.018^{***}	
	(0.006)		(0.001)		(0.006)	
$Leverage_{f,t-1}$	0.010^{**}		0.052^{***}		0.013^{***}	
	(0.004)		(0.001)		(0.004)	
$Debt\ coming\ due_{f,t-1}$	0.082^{***}		0.067^{***}		0.085^{***}	
	(0.025)		(0.004)		(0.025)	
$Average\ CDS_{f,t-1}$	0.335^{***}		0.088^{***}		0.334^{***}	
	(0.028)		(0.005)		(0.028)	
$Log\ assets_{f,t-1}$	0.001		-0.012^{***}		0.001	
	(0.001)		(0.0002)		(0.001)	

Panel B: Second stage for relative credit spreads and incremental funding risks

	$issuance_{fkt}$: Net issuance to assets ratio					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^{r}_{fk,t-1}$: Relative bond-type credit spread	-0.575^{***}	-0.478^{***}			-0.513^{***}	-0.397^{***}
	(0.079)	(0.075)			(0.075)	(0.082)
$\Delta FR_{fk,t-1}$: Incremental funding risk			-0.298^{***}	-1.494^{***}	-0.354^{***}	-0.929^{**}
			(0.109)	(0.430)	(0.114)	(0.414)
$Tobin's\ Q_{f,t-1}$	0.058^{***}		0.054^{***}		0.064^{***}	
	(0.019)		(0.018)		(0.019)	
$Leverage_{f,t-1}$	-0.049^{***}		-0.037^{**}		-0.028^{*}	
	(0.014)		(0.015)		(0.016)	
$Debt\ coming\ due_{f,t-1}$	0.662^{***}		0.637^{***}		0.684^{***}	
	(0.083)		(0.078)		(0.082)	
$Average\ CDS_{f,t-1}$	0.141		-0.028		0.151	
	(0.093)		(0.085)		(0.098)	
$Log\ assets_{f,t-1}$	-0.016^{***}		-0.021^{***}		-0.021^{***}	
	(0.003)		(0.004)		(0.004)	
Firm FE	✓		✓		✓	
Month FE	✓		✓		✓	
Firm × Month FE		✓		✓		✓
F-statistic	96.25	359.52	1257.66	85.96	400.43	289.09
Observations	322,817	322,817	322,817	322,817	322,817	322,817

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

This table shows how relative bond-type credit spreads in the previous period would affect the firm's issuance of bond type k in period t. The sample period is monthly from January 2008 to December 2023, considering the period of any positive outstanding for a given bond type k held by firm f. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The outcome variable is the amount issued for a given bond type k 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 (29) and (1). The instrument variables are constructed from Equation (30) and (34). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

Table E.4: How relative credit spread and funding risk affect firms new bondtype issue

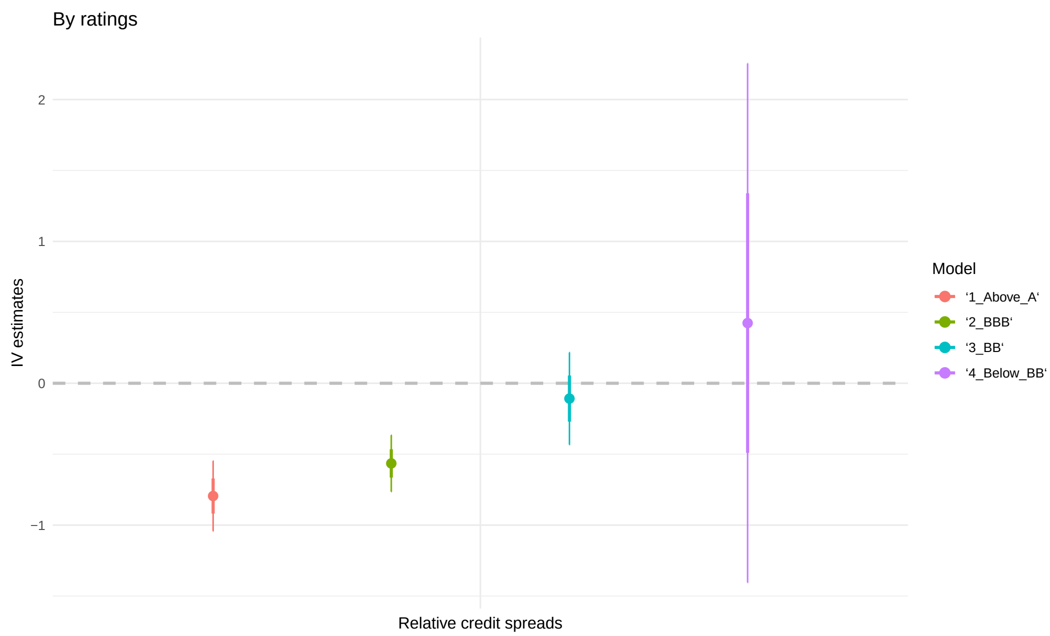
	$\mathbb{1}[new\_bondtype]_{fkt}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$cs^r_{fk,t-1}$: Relative bond-type credit spread	-0.095^{***}	-0.064^{***}			-0.087^{***}	-0.058^{***}
	(0.019)	(0.020)			(0.018)	(0.022)
$\Delta FR_{fk,t-1}$: Incremental funding risk			-0.039^{**}	-0.155^{**}	-0.049^{**}	-0.073
			(0.020)	(0.063)	(0.020)	(0.072)
$Tobin's\ Q_{f,t-1}$	0.002		0.001		0.003	
	(0.005)		(0.004)		(0.004)	
$Leverage_{f,t-1}$	-0.005		-0.003		-0.002	
	(0.004)		(0.004)		(0.004)	
$Debt\ coming\ due_{f,t-1}$	0.114^{***}		0.109^{***}		0.117^{***}	
	(0.022)		(0.021)		(0.022)	
$Average\ CDS_{f,t-1}$	0.033		0.004		0.034	
	(0.023)		(0.019)		(0.022)	
$Log\ assets_{f,t-1}$	-0.001^{**}		-0.002^{***}		-0.002^{***}	
	(0.001)		(0.001)		(0.001)	
Firm FE	✓		✓		✓	
Month FE	✓		✓		✓	
Firm × Month FE		✓		✓		✓
F-statistic	53	359.52	56.23	85.96	400.43	289.09
Observations	322,817	322,817	322,817	322,817	322,817	322,817

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

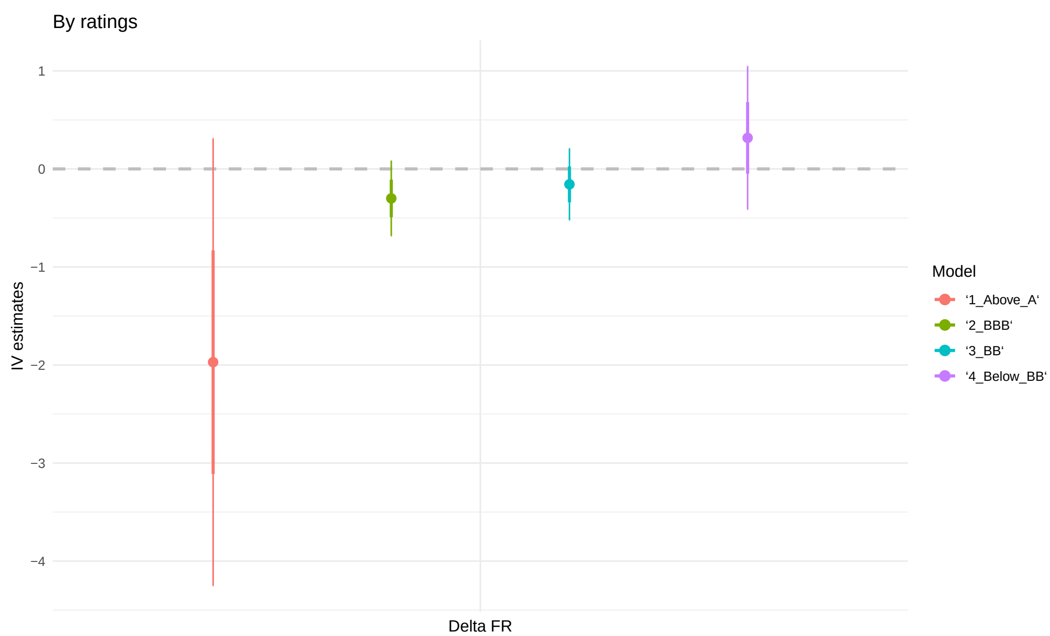
This table shows how variation in demand-based risk would impact firm's decision of issuing a new bond type, conditional on prices. The sample period is monthly from January 2008 to December 2023, considering the period of any positive outstanding for a given bond type k held by firm f. The sample includes non-financial firms that have positive net issuance firm-wide and bonds' remaining time to maturity not smaller than 1 year in period t. The independent variable $\mathbb{1}[new\_bondtype]_{ft} = 1$ if the firm f has no outstanding for bond type k in the past 12 months. The endogenous variables are constructed from Equation (29) and (1). The instrument variables are constructed from Equation (30) and (34). The firm-level controls in columns (2) and (4) include Tobin's Q, leverage, average CDS spread, debt coming due, and log assets in the previous period. We winsorize all the variables at 1% and 99% to remove outliers. Data source: FISD, Compustat, WRDS Bond Returns, NAIC, eMAXX, CRSP, and Markit CDS.

Figure E.3: IV heterogeneous effects: subsample by rating buckets

a. Second-stage estimates on relative credit spreads



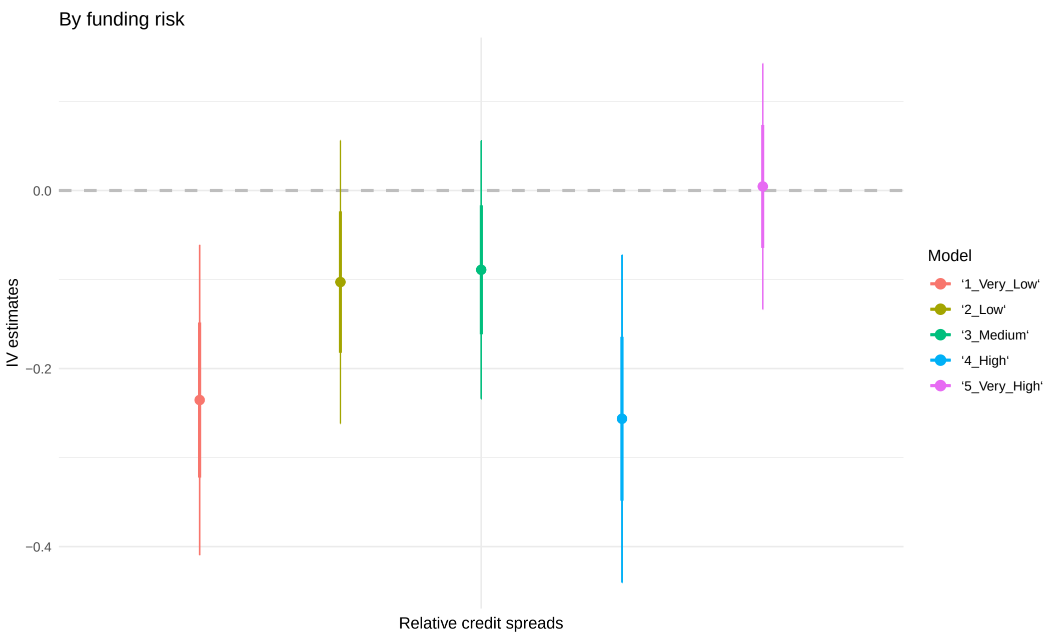
b. Second-stage estimates on demand-based risk



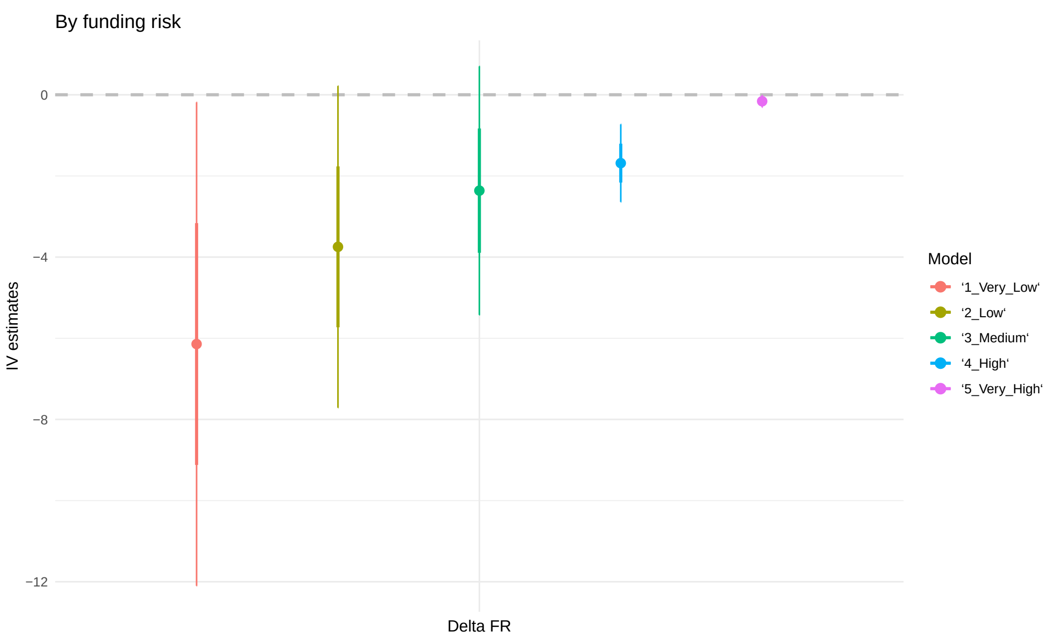
Note: This figure shows the IV heterogeneous effects, subsampling by firms' maximum ratings in the prior period. The endogenous variables are constructed from Equation (29) and (97). The instrument variables are constructed from Equation (30) and (109). We control for firm characteristics including Tobin's 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 monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

Figure E.4: IV heterogeneous effects: subsample by funding risk

a. Second-stage estimates on relative credit spreads



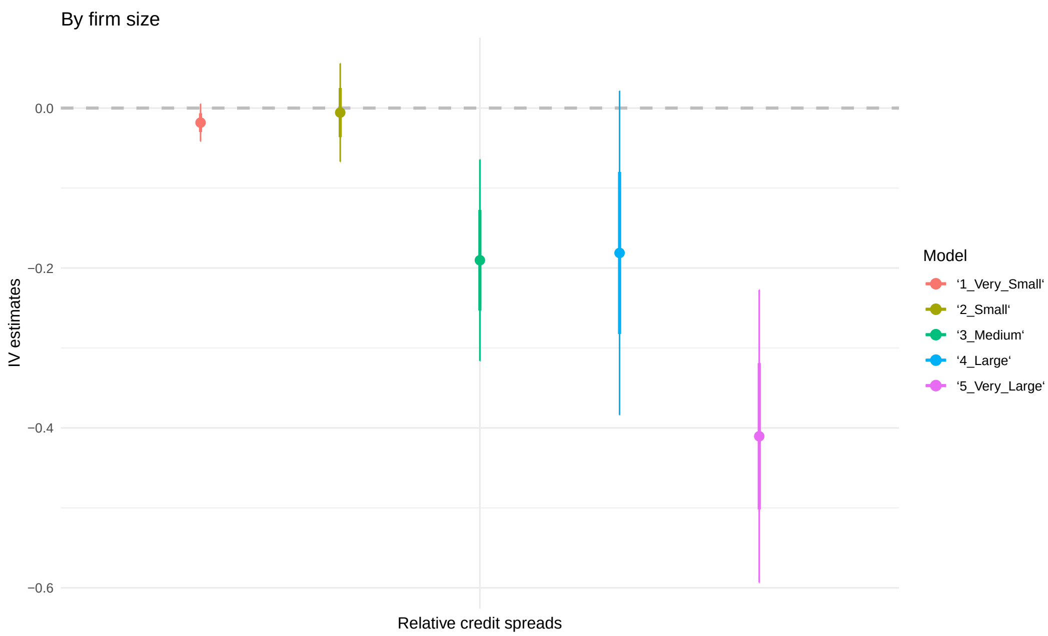
b. Second-stage estimates on demand-based risk



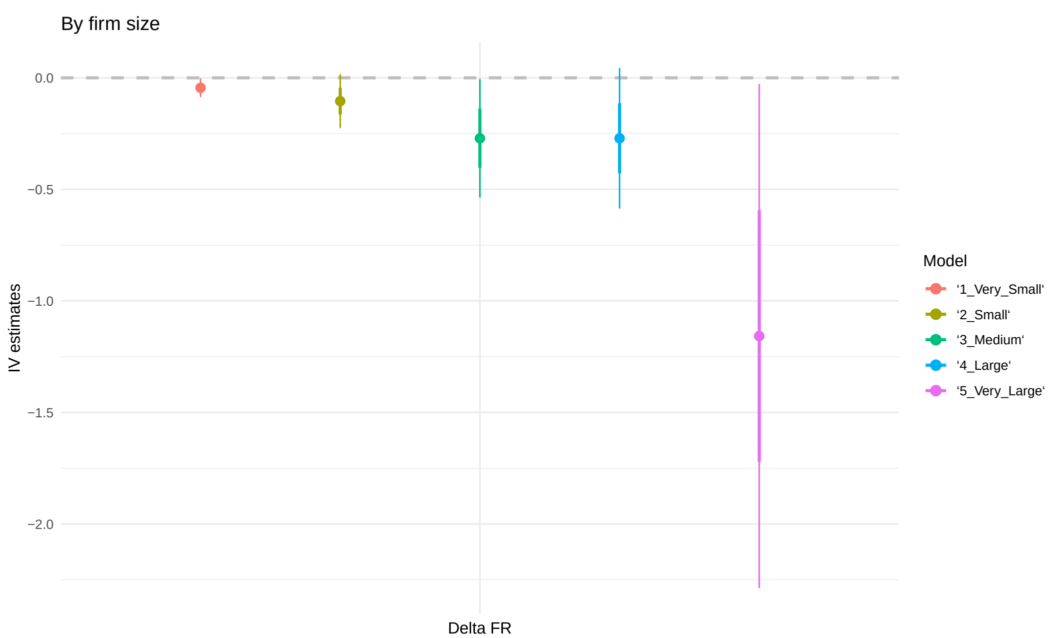
Note: This figure shows the IV heterogeneous effects, subsampling by firms' funding risk in the prior period. The endogenous variables are constructed from Equation (29) and (97). The instrument variables are constructed from Equation (30) and (109). We control for firm characteristics including Tobin's 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 monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

Figure E.5: IV heterogeneous effects: subsample by firm size

a. Second-stage estimates on relative credit spreads



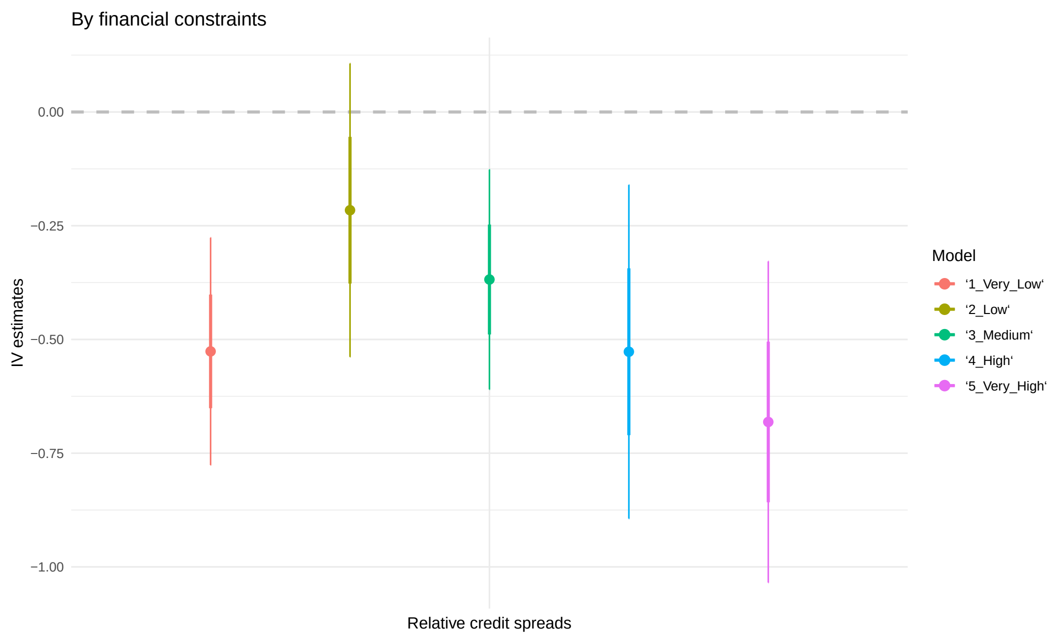
b. Second-stage estimates on demand-based risk



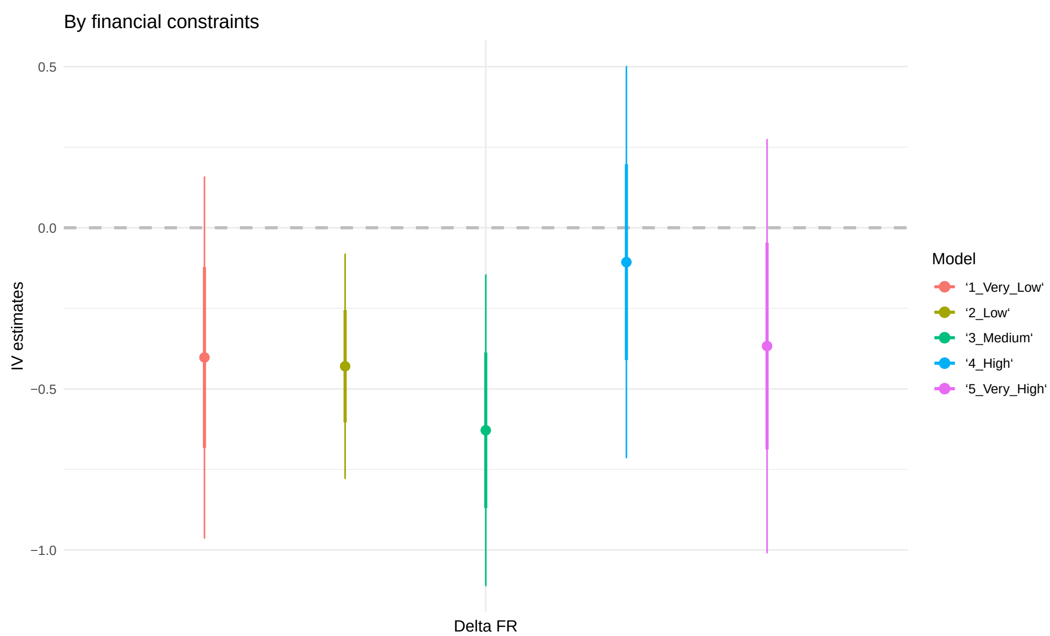
Note: This figure shows the IV heterogeneous effects, subsampling by firms' size in the prior period. The endogenous variables are constructed from Equation (29) and (97). The instrument variables are constructed from Equation (30) and (109). We control for firm characteristics including Tobin's Q, leverage, average CDS, debt coming due, and log assets in the previous period. Firm fixed effect and month fixed effect are included. Data is monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

Figure E.6: IV heterogeneous effects: subsample by financial constraints

a. Second-stage estimates on relative credit spreads



b. Second-stage estimates on demand-based risk

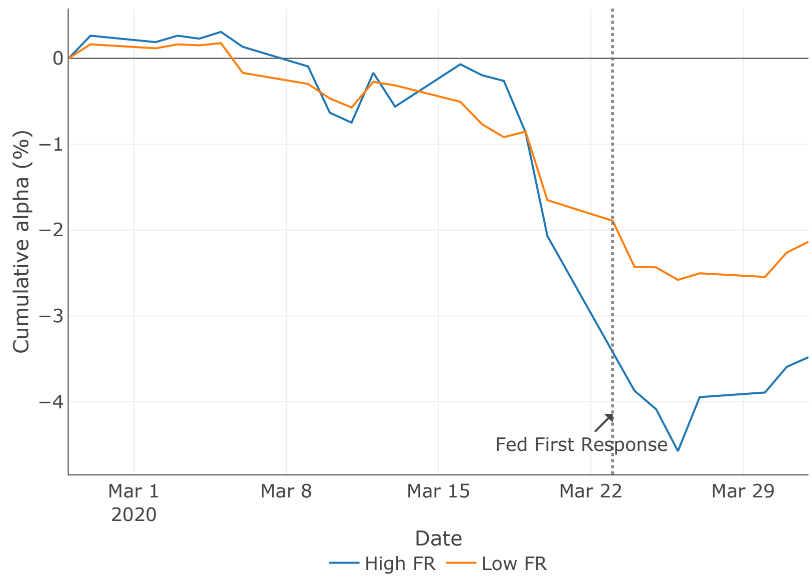


Note: This figure shows the IV heterogeneous effects, subsampling by firms' level of financial constraints in the prior period. The endogenous variables are constructed from Equation (29) and (97). The instrument variables are constructed from Equation (30) and (109). We control for firm characteristics 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 monthly from January 2003 to December 2023. We winsorize all the variables at 1% and 99% to remove outliers.

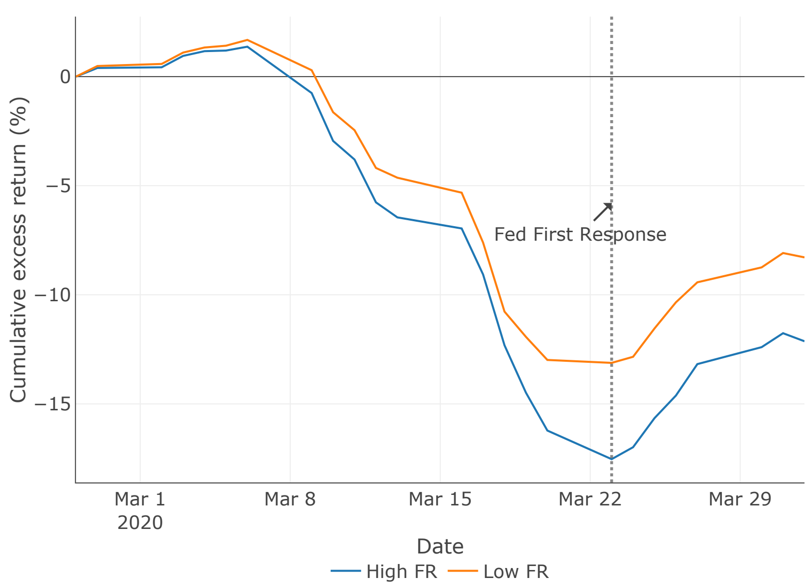
F Impact of Funding Risk in Times of Distress

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

a. Cumulative abnormal returns



b. Cumulative excess returns



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

G Firm sophistication and underwriters

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

$$\begin{aligned} Funding\_Risk_{ft} = \beta \# Underwriters_{ft} + \gamma_1 Age_{ft} + \gamma_2 TobinsQ_{ft} + \gamma_3 Leverage_{ft} \\ + \gamma_4 AvgCDS_{ft} + \gamma_5 DebtDue_{ft} + \gamma_5 TotalAssets_{ft} + \alpha_f + \alpha_t + \varepsilon_{ft} \end{aligned} \tag{98}$$

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

Table G.1: Underwriter analysis

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

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

H Define demand-based risk and funding risk measures

H.1 Define demand-based risk

We define an asset's DBR_t as its time-varying exposure to idiosyncratic demand shocks, leveraging the stable investor base across bond types, and extract diagonal elements as the bond-type k's demand-based risk (dbr):

$$\underbrace{DBR_t}_{K \times K} = \underbrace{S_t'}_{K \times N} \underbrace{\Omega}_{N \times N} \underbrace{S_t}_{N \times K} \tag{99}$$

$$\underbrace{dbr_t}_{K \times 1} = diag(DBR_t) \tag{100}$$

where

$$\underbrace{S_t}_{N \times K} = \begin{bmatrix} \frac{paramt_{A1t}}{paramt_{1t}} & \dots & \frac{paramt_{AKt}}{paramt_{Kt}} \\ \vdots & & \vdots \\ \frac{paramt_{N1t}}{paramt_{1t}} & \dots & \frac{paramt_{NKt}}{paramt_{Kt}} \end{bmatrix} \tag{101}$$

and

$$\underbrace{\Omega}_{N \times N} = Cov(f_n^{\perp}) = \begin{bmatrix} Var(f_A^{\perp}) & \dots & Cov(f_N^{\perp}, f_A^{\perp}) \\ \vdots & & \vdots \\ Cov(f_N^{\perp}, f_A^{\perp}) & \dots & Var(f_N^{\perp}) \end{bmatrix} \tag{102}$$

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 bond-type level instrument z_{kt}^{dbr} similar to the z_{kt}^{cs} in Equation (30), that exploits variation in asset holding shares that arise from exogenous flows:

$$\underbrace{z_t^{DBR}}_{K \times K} = \underbrace{z_t^{cs\prime}}_{K \times N} \underbrace{\Omega}_{N \times N} \underbrace{z_t^{cs}}_{N \times K} \tag{103}$$

$$z_{kt}^{dbr} = \mathbb{1}_k' diag(z_t^{DBR}) \tag{104}$$

where $\mathbb{1}_k$ is a $K \times 1$ vector with all elements equal to 0, except for a 1 in the k-th position, and

$$z_{nkt}^{cs} = \frac{\sum_{i \in I_{kt}^N} \times holdings_{ik,t-1}}{mktcap_{k,t-1}} \tag{105}$$

H.2 Define funding risk

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

$$FR_{ft} = \sqrt{\underbrace{q_{ft}}_{1 \times K} \underbrace{\Sigma_t}_{K \times K} \underbrace{q_{ft}}_{K \times 1}} \tag{106}$$

where q_{ft} is a $K \times 1$ vector of firm's holdings share for each bond-type, normalized by its contemporaneous total assets:

$$\underbrace{q_{ft}}_{K \times 1} = \begin{bmatrix} \frac{amtout_{1ft}}{amtout_{1t}} \times \frac{1}{assets_{ft}} \\ \vdots \\ \frac{amtout_{Kft}}{amtout_{Kt}} \times \frac{1}{assets_{ft}} \end{bmatrix} \tag{107}$$

We then define the incremental ΔFR_{fkt} for each bond-type held by the firm by taking the first-order condition of funding risk:

$$\Delta FR_{fkt} = \mathbb{1}_k' \underbrace{\Sigma_t}_{K \times K} \underbrace{q_{ft}}_{K \times 1} \tag{108}$$

In a similar manner, we construct an instrument $z_{fkt}^{\Delta FR}$ to avoid endogeneity issues:

$$z_{fkt}^{\Delta FR} = \mathbb{1}_k' \underbrace{z_t^{\Sigma} q_{ft}}_{K \times 1} \tag{109}$$

where $\mathbb{1}_k$ is a $K \times 1$ vector with all elements equal to 0, except for a 1 in the k-th position.